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Abstract

Unexpectedly severe winter weather, which is arguably exogenous to firm and bank fundamentals, represents a significant cash flow shock for bank-borrowing firms. Firms respond to these shocks by drawing on and increasing the size of their credit lines. Banks charge borrowers for this liquidity via increased interest rates and less borrower-friendly loan provisions. Credit line adjustments occur within one calendar quarter of the shock and persist for at least nine months. Overall, we provide evidence that bank credit lines are an important tool for managing the non-fundamental component of cash flow volatility, especially for solvent small bank borrowers.

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Weathering Cash Flow Shocks

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ABSTRACT

Unexpectedly severe winter weather, which is arguably exogenous to firm and bank fundamentals, represents a significant cash flow shock for bank-borrowing firms. Firms respond to these shocks by drawing on and increasing the size of their credit lines. Banks charge borrowers for this liquidity via increased interest rates and less borrower-friendly loan provisions. Credit line adjustments occur within one calendar quarter of the shock and persist for at least nine months. Overall, we provide evidence that bank credit lines are an important tool for managing the non-fundamental component of cash flow volatility, especially for solvent small bank borrowers.

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How useful to firms are bank lines of credit? On one hand, Shockley and Thakor (1997) and Holmstrom and Tirole (1998) argue that credit lines precommit banks to provide debt financing when firms face negative shocks. On the other hand, Sufi (2009) finds that access to credit lines is restricted following declines in borrower profitability – presumably just when firms most need the financing. Acharya et al. (2014) explain this behavior by showing that credit line revocation can serve a liquidity monitoring role, making it optimal for banks to revoke credit lines when firms most need the credit.[1]

This paper examines firms' use of credit lines when they face a particular type of liquidity shock that is not directly related to fundamentals. The shock arises from abnormally heavy winter snowfall, which disrupts distribution channels and increases operating costs, but does not cause firms to have long-term operational problems. Focusing on weather-induced cash flow variability allows us to isolate a pure liquidity shock and largely avoid the confounding effects of changes in firm's long-term profitability on its credit needs and the supply of credit from banks. We find that bank borrowers, particularly financially solvent small firms, rely extensively on credit lines to manage these cash flow shocks and that lenders charge borrowers for this liquidity provision, providing the first direct evidence that firms use credit lines as liquidity insurance against cash flow volatility that is unrelated to firm fundamentals.

Our analysis uses a novel dataset of bank loan portfolios that the Federal Reserve has collected since 2012. The dataset contains detailed information on bank loan contracts at the quarterly frequency, including credit line limits, credit line utilization, and bank loan characteristics. In addition, it typically includes a range of borrower characteristics, such as operating income and total assets, at an annual frequency. Because the dataset covers the full set of firms in a bank's loan portfolio with outstanding loan commitments of at least $1 million, our sample includes more small firms than most other research on corporate liquidity management. In our sample the average credit line is 24% of total assets, which is approximately 50% larger than the corresponding average for the publicly traded firms

[1] Also see the model and discussion in Almeida et al. (2014).

studied in Sufi (2009).

This sample offers a unique opportunity to study how the typical bank-borrowing firm uses credit lines as a liquidity management tool. To address the question of whether credit lines are used to manage cash flow shocks that are exogenous to firm and market conditions, we introduce abnormally severe local winter weather as a shock to corporate cash flows. We obtain data on winter weather at the county level from the National Oceanic and Atmospheric Administration (NOAA). We find that abnormally-severe winter weather significantly affects total *annual* firm-level cash flows. For example, a one standard deviation increase in a county's abnormal snow cover in January thru March reduces the annual cash flow of firms headquartered in that county by 0.22% of total assets. Partitioning by industry, we find a negative relation between snow cover and cash flow in each of the top eight sectors that collectively comprise 87% of our sample. The effect is statistically significant at the 10% level or better for the transportation, real estate, construction, manufacturing, retail, and (using a secondary measure of abnormal snow cover) wholesale industries. Given that we find no significant relation between abnormal snow cover and sales, our findings are consistent with severe winter weather increasing operating costs for firms in industries that operate predominantly outdoors and/or are reliant on a transportation-dependent supply chain.

We employ two different empirical approaches to investigate how firms manage weather-induced cash flow shocks. First, we use the abnormal winter snow cover in the county of a firm's headquarters as an instrumental variable (IV) for annual cash flows. This allows us to examine the relation between cash flow shocks and end-of-year corporate outcomes, such as credit line draws, credit line size adjustments, and changes in cash, working capital, and trade credit. Second, we estimate the direct relation between abnormal winter snow cover and credit line outcomes. One key benefit of this reduced form approach is that we can study credit line usage within a larger and more complete panel of firms because we do not lose observations with missing or inconsistent financial statement information. In either case, our identifying assumption is that severe winter weather affects corporate liquidity management only through its effect on current cash flows. The temporary nature of our severe winter weather measure makes this assumption plausible. Unlike highly destructive natural disaster events such as hurricanes or earthquakes, abnormal snow cover is unlikely to affect investment opportunities or access to capital, except through its affect on the cash flows of current projects. Our empirical results are similar if we exclude the most extreme snow events (which may affect firm fundamentals for reasons other than reduced cash flows).

The purpose of our two-stage least squares (2SLS) procedure is to isolate the causal effect of a one dollar change in cash flows. As such, a magnitude of 1 (in absolute value), which indicates that the second stage outcome changes dollar for dollar with weather-induced changes in cash flow, is a natural benchmark for evaluating our coefficient estimates. We estimate that, on average, annual credit line draws increase by approximately 50 cents for every $1 reduction in annual cash flow. In addition, the IV estimates indicate a significant negative relation between cash flow and changes in credit line limits of similar magnitude. Our reduced form estimates are qualitatively similar: abnormal snow cover is positively and significantly related to credit line draws and changes in credit line size. These results are driven by the sub-set of firms who actively use credit lines and have little excess slack at the time of the cash flow shock. Overall, our findings show that bank borrowers rely extensively on credit lines to manage non-fundamental cash flow shocks, and that banks accommodate borrowers who draw down their credit lines by adjusting credit line limits.

To investigate whether firms in our sample also use cash to buffer weather-induced cash flow shocks, we employ the same 2SLS approach with change in cash holdings as the second stage dependent variable. We find a statistically insignificant end-of-year cash balance decrease of approximately 18 cents for every $1 decrease in annual cash flow. We also find insignificant relations between cash flow and changes in both non-cash working capital and trade credit. The fact that these outcomes are measured at the end of the year means that there may be a short-run role for cash, working capital, or trade credit in managing unanticipated cash flow shocks, however by the end of the calendar year there is no significant change along these dimensions.

To better understand the timing of credit line responses to abnormal winter weather, we regress quarterly credit line outcomes directly on abnormal winter snow cover. We find that firms respond to abnormal snow in the first calendar quarter by drawing on their credit line in the first half of the year and expanding the size of credit lines in the second quarter (i.e., between April 1 and June 30). Consistent with our regression results on annual credit line use, there is no reversal in the next two quarters, suggesting that firms use credit lines to address liquidity needs in the nine months following short-term shocks. We also find no evidence that borrowers anticipate future abnormal snow as there is no relation between credit line activity and next year's abnormal snow.[2]

We next examine whether banks adjust interest rates or other loan contract provisions when providing liquidity for non-fundamental cash flow shocks. We find that interest rates increase following weather-induced cash flow reductions. In addition, loans become shorter in maturity, more likely to be secured, and less likely to have fixed interest rates.[3] Thus, one reason that banks accommodate borrowers' liquidity demands following exogenous cash flow shocks appears to be that they can charge borrowers for this service, both in terms of higher interest rates and less borrower-friendly loan terms.

Finally, we examine whether firms' reliance on credit lines as a tool for managing exogenous cash flow shocks varies by borrower size, credit quality, or the geographical distance between the borrower and the lender. We find that the statistical significance of our main results (i.e., the credit line draws, the credit line expansion, and the interest rate increase) is concentrated in the 80% of our sample with below $100 million in total assets. In addition,

[2]We further support our identifying assumption that borrowers do not anticipate future abnormal snow by showing that immediately prior to the realization of the shock borrower-years experiencing positive abnormal snow shocks are observably similar to borrowers-years experiencing negative shocks.

[3]Data limitations prevent us from examining the use of loan covenants.

the results are strongest for firms located in close geographical proximity to their lenders. Finally, we find no significant effects among the lowest credit quality borrowers (i.e., the 19% of our sample with ratings of B or lower). Although these partitions are endogenous and not mutually exclusive, they provide some descriptive support for the idea that bank credit is a particularly important source of liquidity for smaller local firms (e.g., Berger and Udell (1995)) but may not be available for borrowers with high credit risk (e.g., Diamond (1991)).

Our findings provide novel evidence that, for solvent smaller firms, bank credit lines are an important tool for managing the non-fundamental component of cash flow volatility.[4] Despite the widespread use of credit lines, most prior evidence comes from surveys or studies of how larger firms use credit lines when facing severe financial market disruptions or dealing with long-term operational problems.[5] Another key feature of the existing literature is a focus on how credit lines are used to manage general (overall) cash flow volatility, which is driven by both endogenous and exogenous factors. This makes simple Ordinary Least Squares (OLS) regressions of credit line use on cash flows difficult to interpret.[6] Regressing credit line use directly on cash flows (and our full set of control variables) in our sample exemplifies the importance of these confounding factors; OLS estimates indicate that cash flows are unrelated to credit line draw downs and positively related to credit line size, which differs substantially from the large negative effects we document in the 2SLS regressions.

In addition to being consistent with theories arguing that credit lines are a valuable and efficient liquidity management tool (e.g., Shockley and Thakor (1997); Holmstrom and Tirole (1998)) and that banks are ideal providers of this liquidity (e.g., Kashyap et al. (2002);

[4]See Acharya et al. (2013), Jimenez et al. (2009), Yun (2009), Lins et al. (2010), Demiroglu et al. (2012), and Demiroglu and James (2011) for evidence on other uses of credit lines.

[5]For example, see Sufi (2009), Ivashina and Scharfstein (2010), Campello et al. (2011), Campello et al. (2012), Acharya et al. (2014), and Berospide and Meisenzahl (2016).

[6]For example, negative profitability shocks can lead to less credit line usage because of covenant violations and bank monitoring (e.g., Sufi (2009); Acharya et al. (2014); Gustafson et al. (2019)), or greater credit line usage via a liquidity management mechanism (e.g., Holmstrom and Tirole (1998); Campello et al. (2011)).

Gatev and Strahan (2006)), our findings also contribute to the broader liquidity management literature (e.g., Almeida et al. (2004); Denis and Sibilkov (2010); Campello et al. (2011)). As Almeida et al. (2014) discuss, this literature emphasizes the increasing importance of cash holdings as a liquidity management tool, particularly for financially constrained firms that face large aggregate liquidity risks. By showing that banks provide liquidity insurance to smaller local firms that are susceptible to cash flow shocks but not in a position to fully manage them with internal funds, our findings relate to the large literature on the value of lending relationships, suggesting a specific channel through which banking relationships are valuable.[7]

Finally, we contribute to a growing literature on the effects of natural events on firm decision-making and economic activity (e.g., Giroud et al. (2012); Bloesch and Gourio (2015); Chen et al. (2017); Dessaint and Matray (2017)). We identify an important role of banks in helping small firms deal with these unanticipated weather events. In so doing, our work complements recent evidence showing that local banks play an important role in mitigating the negative effects of natural disasters (Cortes (2014); Cortes and Strahan (2016); Koetter et al. (2019)).

The remainder of the paper is organized as follows. Section I describes the sample and data. Sections II and III discuss the relation between severe weather and corporate cash flows as well as how this supports our identification strategy. Section IV presents our main results, which provide evidence on how firms manage exogenous cash flow shocks. Section V examines how cash flow shocks impact bank loan provisions and Section VI explores heterogeneity in our main results. Finally, Section VII concludes.

[7]A number of studies explore the impact and value of lending relationships, particularly for smaller firms. For example, see James and Wier (1990), Petersen and Rajan (1994), Berger and Udell (1995), Petersen and Rajan (1995), Blackwell and Winters (1997), Houston and James (2001), Ongena and Smith (2001), Petersen and Rajan (2002), Berger et al. (2005), and Fuss and Vermeulen (2008).

I. Data Construction and Sample Descriptive Statistics

A. *Federal Reserve's Y-14Q collection*

Our main data source is Schedule H.1 of the Federal Reserve's Y-14Q data collection. This data collection began in June of 2012 to support the Dodd-Frank Stress Tests and the Comprehensive Capital Analysis and Review. The reporting panel includes bank holding companies exceeding US $50 billion in total assets. The 35 institutions in the Y-14 collection provide loan-level data on their corporate loan portfolio whenever a loan exceeds $1 million in commitment exposure.[8] We restrict the sample to domestic borrowers, excluding government entities, individual borrowers, foreign entities, and nonprofit organizations.

The dataset contains quarterly information on bank loan characteristics and annual information from borrowers' financial statements. Thus, our analyses using firm-level characteristics require a firm-year panel.[9] To compute borrower-level outcomes within this firm-year panel, we aggregate all loan-level variables across all lenders in a given borrower-year.[10]

For many of our empirical analyses we require data on changes or levels of financial variables such as total assets, fixed assets, cash and marketable securities, non-cash working capital, total liabilities, total sales, total debt, accounts receivable, accounts payable, and EBITDA, which we use as our measure of cash flow. In addition, we require at least two

[8]As Bidder et al. (2016) document, the commercial loans in the Y-14 data represent approximately 70% of all commercial loans extended in the United States.

[9]To avoid duplicate observations (due to some firms reporting their financials more than once in the year) we keep the financial statement information with a reporting date closest to the end of each calendar year, which typically are the financials as of Q4.

[10]This aggregation may bias the total bank borrowing of large firms downward to the extent that their loans are syndicated to non-Y14 banks, smaller banks, and nonbanks. This bias is mitigated by the fact that syndicated credit lines are almost always held by banks and Y-14 reporting banks participate in approximately 98% of all banks credit line exposure in the Shared National Credit data between 2011 and 2015. Therefore, changes in the committed and utilized shares of Y-14 banks are likely to mirror changes in overall credit lines.

consecutive years of bank financing information so that we can compute changes in credit line limits and utilization. After imposing these restrictions, our sample consists of 102,742 firm-year observations during the period 2012 to 2016. We also replicate all of our results with an expanded sample, which relaxes the requirement of financial statement information. This sample, which only requires information on bank borrowing, contains up to 189,312 borrower-year observations.[11] We winsorize all financial and loan variables with the exception of loan interest rate at the 1^{st} and 99^{th} percentiles to mitigate the effect of outliers. Before collapsing the loan-level data to the borrower-year level, we trim the interest rate variable at the 1^{st} and 99^{th} percentiles to eliminate data errors. See Appendix A for more detailed description of the data cleaning.

B. Descriptive Statistics

Table I reports descriptive statistics for the sample with complete financial statement reports. Small firms dominate our sample. The 75^{th} percentile of the book value of total assets is \$92.64 million, and the average size of firms falling below this threshold is only \$22.22 million. The firms we study are thus substantially smaller than the majority of firms in studies using COMPUSTAT and survey data. For example, Campello et al. (2011) consider firms "small" if their sales are less than \$1 billion, whereas the 75^{th} percentile of sales in our sample is \$170.59 million (unreported), corresponding to 3.03 times total asset value.

The firms in our sample are more levered than the typical COMPUSTAT firm, with average liabilities- and total debt-to-assets ratios of approximately 61% and 32%, respectively. This extensive reliance on bank debt is likely magnified by our sample being restricted to bank borrowing firms, but is broadly consistent with the evidence on small-firm borrowing in Robb and Robinson (2014).

[11] For some of our analyses that do not require firm financials, we further expand the sample to a firm-year-quarter panel of bank debt characteristics in order to more precisely pin down the timing of credit line usage.

The average credit line size is approximately 24% of total assets, which is considerably larger than the average ratio of credit line commitments to total assets among the publicly-traded firms reported in recent studies (e.g., Sufi (2009)). There is also substantial variation in line size. The 75^{th} percentile of credit line size is approximately 35% of total assets, while the 25th percentile is only 9%. Average (median) cash holdings are 10% (5%) of total assets, which is somewhat less than the typical public firm (e.g., Bates et al. (2009)).

II. Severe Weather and Cash Flow

There is ample anecdotal evidence suggesting that abnormally severe weather may negatively impact firm cash flows, even at the annual level. This idea manifested during the abnormally cold winters in the Northeast United States during 2014 and 2015. A CNBC report in February of 2014 on the manufacturing sector contains a long list of companies detailing the impact of severe winter weather. For example, Fabricated Metal Products cited poor weather impacting their outbound and inbound shipments, and Plastics & Rubber Products stated that they experienced many late deliveries due to truck lines being shut down.[12] There is also no shortage of anecdotes in other industries. For example, Todd Smith, VP Sales, at Leonard's Express, a mid-sized trucking company summarizes the effect that winter storms can have in his industry, stating "a midsized trucking company can easily see a financial hit in the tens of thousands of dollars per day" due to factors such as fuel and equipment expenses, snow removal, and accident costs.[13]

To the extent that severe winter weather has an impact on cash flow, it provides a unique opportunity to investigate the role of credit lines in managing non-fundamental cash flow shocks. The reason for this is that unexpectedly bad winter weather is unlikely to impact

[12] See the February 5, 2014 article entitled "Here's how bad winter weather is hurting the economy" by Kristen Scholer, which can be found online at http://www.cnbc.com/2014/02/05/heres-how-bad-winter-weather-is-hurting-the-economy.html

[13] See http://blog.chrwtrucks.com/carrier/winter-weather-a-trucking-company's-perspective-2/

long-run firm outcomes except through its effect on the cash flows of current projects. This is especially true if the severe weather is measured over a relatively short interval and extreme severe weather incidents, which may destroy a jurisdiction's infrastructure and affect the firm's long-run growth prospects, are excluded from the measure.

A. Measuring Severe Winter Weather

There are a variety of ways to measure severe winter weather, and the extent to which severe winter weather affects corporate cash flow is an empirical question. We use normalized measures of severe winter weather, capturing the component of winter weather that firms are not already prepared for. Our primary measure of abnormal weather is based on the average daily snow cover during the first quarter of each year, although results are similar using the 95^{th} percentile of daily snow cover during the first quarter (i.e., the snow cover on the fourth snowiest day of the quarter). The reason we choose snow cover as our main measure is because it combines the intuitive negative effects that both snowfall and cold winter weather may have on firms' cash flows.

We construct these measures using county-level data on daily snow cover (in inches) from the NOAA's website. The NOAA reports daily snow cover (SNWD) for each weather station in the United States. For each day and county, we first compute the average value of snow cover across weather stations. Results are similar using the median. We then calculate the average and 95^{th} percentile of daily snow cover in each county-quarter between 2000 and 2016. We aggregate these values into a baseline average of snow cover in the first calendar quarter for each county-year using data from the previous 10 years. Results are robust to defining benchmark weather conditions using a fixed ten year period from 2001 through 2010.

We define *Abnormal Snow* as the difference between the average daily snow cover during the first quarter in a given county-year minus the county's average daily snow cover in the first quarter during the previous ten years. *Abnormal Snow* 95 is defined similarly using the 95^{th} percentile (instead of the average) of daily snow cover in the first quarter.

Panels A and B of Figure 1 present the distribution of these two abnormal snow measures over our sample period. For the sake of presentation, all of these metrics are divided by 1,000. The figures show a large dispersion in abnormal snow during our sample period, and show that there are a significant number of observations with extreme outcomes. There is also a large cluster of abnormal snow cover observations near zero.

Our results are not sensitive to trimming the abnormal snow measures at 3 standard deviations (which drops approximately 8.5% of observations) or dropping areas that experience no snow cover in the previous ten years. Thus, our results are not driven by the most severe or unexpected winter weather events. A byproduct of our results being driven by marginal changes in winter snow cover (as opposed to devastating blizzards or hurricanes) is that it is reasonable to assume that our abnormal snow measures are unrelated to a borrower's future investment opportunities or a lender's ability to supply liquidity.

B. Abnormal Weather and Cash Flow

Although our abnormal snow measures are unlikely to affect the attractiveness of future investments, it is possible that winter snow cover affects the cash flows of ongoing projects. To investigate this empirical question, we regress annual cash flow on abnormal snow cover, firm-specific control variables, and a set of industry x year-quarter and county fixed effects. Therefore, we identify the effect of winter weather on cash flows using only within-county severe weather variation over time, while the industry x year-quarter fixed effects control for macro-economic conditions even to the extent that they affect specific industries (defined at the 4-digit NAICS level). Notably, to the extent that the effects of first quarter snow storms reverse before the end of the year we expect to find no relation between abnormal winter snow cover and annual cash flows. Equation 1 details this specification:

$$
\begin{aligned}
Cash\ Flow_{it} =& \alpha_0 + \alpha_1 Abnormal\ Snow_{jt} + \alpha_2 Fixed\ Assets_{it-1} + \\
& \alpha_3 Log(Assets)_{it-1} + \alpha_4 Leverage_{t-1} + \alpha_5 Sales_{t-1} + \\
& \alpha_6 Cash_{t-1} + \alpha_7 Debt_{t-1} + \alpha_8 WorkCap_{t-1} + \boldsymbol{\gamma X} + \varepsilon_{it},
\end{aligned} \tag{1}
$$

where $Cash\ Flow_{it}$ denotes the cash flow (i.e., EBITDA) realization of firm i in year t, and $Abnormal\ Snow_{jt}$ denotes the abnormal snow cover in Q1 for county j corresponding to the location of the headquarters of firm i at time t. We include a standard set of firm control variables, which we formally define in Appendix B. All of these controls are measured as of the beginning of the period over which cash flow is measured. $\boldsymbol{X}$ is a vector of 4-digit NAICS industry x year-quarter and county fixed effects.

Table II reports estimates of Equation 1. Comparing Column 1 with Column 2 and Column 3 with Column 4 shows that the inclusion of control variables has little effect on the relation between severe winter weather and corporate cash flows. This evidence is consistent with our measures of abnormal snow triggering cash flow shocks that are unrelated to pre-shock firm fundamentals.

Across all four columns there is a negative and statistically significant relation between abnormal snow cover and corporate cash flows. Focusing on Columns 2 and 4, which include the full set of control variables, *Abnormal Snow* and *Abnormal Snow* 95 both have t-statistics of approximately −4.4. Given that the standard deviation of *Abnormal Snow* is 0.0784, the coefficient of −0.028 in Column 2 suggests that a one standard deviation increase in average snow cover results in an annual cash flow decrease of approximately 0.22% of total assets. A cash flow shock of this magnitude is approximately 0.011 standard deviations of annual cash flow (or 1.4% of average cash flow), consistent with abnormally severe winter weather having an important impact on total annual corporate cash flows.

Undoubtedly, there is significant heterogeneity in the effect of *Abnormal Snow* on cash flows. The small and mid-sized firms in our sample are more likely to be affected by county-level measures of abnormal snow than large firms because their operations will be more concentrated around the corporate headquarters. For example, we find no consistent evidence that abnormally severe winter weather in the headquarter county of COMPUSTAT firms significantly affects annual cash flows. In addition, although a negative relation between cash flows and severe winter weather can be rationalized across a wide range of industries, the magnitude of the relation will likely vary by industry.

To examine this heterogeneity, Table III presents separate estimates of Equation 1 for the eight sectors contributing at least 4% of the borrower-year observations. Given these are within-industry specifications, we include state and year fixed effects and the standard errors are adjusted for heteroskedasticity. In each of these eight sectors there is a negative relation between both measures of abnormal snow cover and cash flow. The effect is statistically significant at the 10% level or better in the transportation, real estate, construction, and retail sectors using either measure of abnormal snow. In addition, transportation, real estate and construction account for three of the four largest coefficients using *Abnormal Snow* and the three largest coefficients using *Abnormal Snow* 95.[14] The coefficients in the wholesale and manufacturing sectors are each statistically significant using one of the two measures.

To better understand the cross-industry variation in the relation between abnormal snow and corporate cash flows, Appendix Table AI replicates Table III using sales, instead of cash flow, as the dependent variable. None of the coefficient estimates are statistically significant and more than half are positive. Thus, the relation between abnormal snow and cash flows is driven by severe winter weather increasing companies' operating costs. Inspecting the industries for which cash flows are most impacted by winter weather reveals two common themes –industries with significant outdoor operations and industries reliant on a supply chain that operates extensively outdoors (see Cachon et al. (2012)).

[14]The third largest coefficient using *Abnormal Snow* is in the business services sector. This coefficient is statistically insignificant.

III. Identification Strategies

The results in Section II show that abnormal snow leads to a reduction in annual cash flows. In this section, we introduce two empirical strategies to identify how firms manage these weather-induced cash flow shocks.

A. Two-stage Least Squares

Our first empirical strategy is a two-stage least squares (2SLS) procedure. The first stage is identical to that in Table II, with our primary specification being the model using *Abnormal Snow* and a full set of firm control variables (reported in Column 2). *Abnormal Snow* must be a sufficiently strong predictor of annual cash flows to mitigate weak instrument concerns. The partial F-statistic on *Abnormal Snow* in Column 2 of Table II is approximately 20, making it unlikely that we encounter bias due to a weak instruments problem. For example, Table 2 in Stock and Yogo (2005) shows that, under certain assumptions, the potential bias of the IV estimate attributable to weak instruments is less than 10% of the size of the IV coefficient whenever the first-stage F-statistic is 16 or higher.

In the second stage we regress corporate outcomes, many of which relate to bank borrowing, on the predicted value from this first stage regression and the same set of controls (minus our instrumental variable, *Abnormal Snow*) that we use in the first stage. Formally, we estimate the following system of equations:

$$\begin{aligned}
Cash\ Flow_{it} =& \alpha_0 + \alpha_1 Abnormal\ Snow_{jt} + \alpha_2 Fixed\ Assets_{it-1} + \\
& \alpha_3 Log(Assets)_{it-1} + \alpha_4 Leverage_{t-1} + \alpha_5 Sales_{t-1} + \\
& \alpha_6 Cash_{t-1} + \alpha_7 Debt_{t-1} + \alpha_8 WorkCap_{t-1} + \boldsymbol{\gamma X} + \varepsilon_{it},
\end{aligned} \tag{2a}$$

$$\begin{aligned}
Y_{it} =& \beta_0 + \beta_1 \widehat{Cash\ Flow}_{it} + \beta_2 Fixed\ Assets_{it-1} + \beta_3 Log(Assets)_{it-1} + \\
& \beta_4 Leverage_{t-1} + \beta_5 Sales_{t-1} + \beta_6 Cash_{t-1} + \\
& \beta_7 Debt_{t-1} + \beta_8 WorkCap_{t-1} + \boldsymbol{\delta X} + \epsilon_{it}
\end{aligned} \tag{2b}$$

where Y_{it} represents the second stage outcome of interest, such as credit line drawdowns, change in credit line limit, or change in cash. As in our first stage (i.e., Equation 1) we include industry-time and county fixed effects. County fixed effects control for the possibility that over our six year sample period some counties had a string of bad weather. Including county fixed effects prevents spurious correlations between credit line use and these (arguably random) strings of bad weather from influencing the estimated relation between *Abnormal Snow* and our outcomes of interest. We control for time-invariant firm-level heterogeneity by defining the dependent variable in terms of within firm changes. In robustness tests and reduced form estimates of the direct relation between *Abnormal Snow* and credit line usage (see Section B) we find qualitatively similar estimates using firm fixed effects. Due to our short unbalanced panel, the inclusion of firm fixed effects substantially reduces statistical power (the degrees of freedom drop from 100,922 to 48,762) resulting in a three- to four-fold increase in standard errors for our 2SLS estimates. As we discuss below, this is less of an issue with our reduced form analysis, which uses a larger sample since it does not require complete financial statement information.

We cluster the standard errors at the 4-digit NAICS industry level. This clustering accounts for within industry correlation in investment opportunities and liquidity demands, either of which may result in correlated use of credit lines. In unreported tests, we replicate our analyses double clustering by county-year and industry. This double clustering accounts for the possibility that credit line use is correlated among firms in the same county at the same time, perhaps due to variation in local economic conditions or winter weather. Because this double clustering generally leads to smaller standard error estimates and affects none of our inferences, we use the (more conservative) industry-level clustering throughout our analysis.

Under certain assumptions, this 2SLS analysis will identify the marginal effect of weather-induced cash flow shocks on the second stage outcome. In addition to the testable assumption that *Abnormal Snow* is a significant enough predictor of corporate cash flows, we must assume that weather-induced shocks only affect the outcomes of interest through their effect on cash flows. Although this exclusion restriction is not directly testable, it is intuitive –an abnormally cold or snowy winter is unlikely to materially impact the profitability of future projects or a firm's access to capital, but (as we find in Section II) does affect the cash flows of current projects. This is an important benefit of using abnormal snow cover, as opposed to more extreme weather events, such as hurricanes.

One way this identifying assumption may be violated is if firms can predict and prepare for abnormally severe winter weather. To the extent they can, severe winter weather may directly affect a variety of corporate decisions. To mitigate this possibility our measure of abnormal winter weather, *Abnormal Snow*, is normalized by the county average snowfall over the previous ten years. In Appendix Table AII we show that this measure exhibits no autocorrelation within a county over time.

To further examine the extent to which firms prepare for abnormal winter weather, we partition the descriptive statistics on our instrument *Abnormal Snow*. Table IV shows that the borrower-years leading up to negative and positive weather shocks are similar along observable dimensions. Average annual cash flows to assets are 0.16 in all 3 terciles of

Abnormal Snow. Leverage, the ratio of fixed-to-total assets, sales-to-assets, cash-to-assets, and working-capital-to-assets are also very similar across the terciles. On average, firm-years in the first tercile are approximately 10% larger in terms of total assets, but at the median this difference is smaller and not economically significant ($21.7 versus $20.2 in total assets). In Column 7 we show that firms in the first and third terciles of the weather shock are economically and statistically similar across observable characteristics after controlling for county and industry-year-quarter fixed effects. Five of the eight control variables we examine (cash flow, leverage, fixed assets, cash, and working captital) are identical to the third decimal point in the first and third terciles in the year prior to the shock. The only difference that is statistically significant at the 5% level is sales-to-assets, but the difference is economically small (less than 0.5% of the average sales-to-assets ratios).

In Table AIII we examine whether historical exposure to significant winter snowfall affects how firms use their credit lines. Specifically, we present average credit line drawn amounts by industry-calendar quarter for firms located in areas in the top, middle, and bottom terciles of historical snow cover. We find little evidence of differential credit line use in areas exposed to more snow. Overall, exposure to severe winter weather does not appear to concentrate around a specific type of firm or result in long-term changes in firms' liquidity management policies, which supports our identifying assumptions.

B. Reduced-form

An important limitation to the 2SLS analysis is that the requirement for complete financial statement information (including the firm's cash flows) significantly reduces the sample size (by around 45%) and biases the sample toward larger firms. The reduction in sample size occurs because we lose some firms entirely, while for other firms full financials are missing in some, but not all, years.

To overcome this limitation of our 2SLS sample, we introduce a second identification strategy in which we regress our second stage outcomes directly on *Abnormal Snow*. This reduced-form specification does not require financial statement information, which greatly expands the sample and provides a more complete panel of firm-year observations, giving us more statistical power to include firm fixed effects (in addition to the 4-digit NAICS industry x year-quarter fixed effects).

Specifically, we estimate the following equation:

$$Y_{it} = \gamma_0 + \gamma_1 Abnormal\ Snow_{jt} + \boldsymbol{\theta X} + \varepsilon_{it}, \tag{3}$$

where $\boldsymbol{Y_{it}}$ is the outcome variable of interest and $\boldsymbol{X}$ contains firm and industry x year-quarter fixed effects. Under the same identifying assumptions that underly our 2SLS procedure, any relation between *Abnormal Snow* and firm-level outcomes is due to the effect of *Abnormal Snow* on the firm's cash flows.

IV. Managing Exogenous Cash Flow Shocks

Most evidence on credit lines is based on samples of larger firms and/or includes firms facing long-term operational problems. This evidence sheds little light on role of banks and credit lines in helping solvent firms manage short-run liquidity shocks. In this section we abstract away from the complex relations between cash flow volatility, long-term profitability, and credit line access, honing in on the liquidity role of credit lines in managing cash flow shocks that are arguably exogenous to borrower and lender fundamentals.

A. Credit Line Drawdowns

In Panel A of Table V we investigate the extent to which firms draw down credit lines when facing a weather-induced cash flow shock. Column 1 of Table V presents an OLS regression in which the dependent variable is the year over year change in drawn credit line amount scaled by the beginning of period total assets. The explanatory variable of interest is cash flow. The OLS analysis in column 1 reveals no significant relation between cash flow and credit line drawdowns, with a point estimate of -0.000 in magnitude. It is difficult to pinpoint the driving forces behind this estimate given the correlation between cash flows and omitted variables, such as investment opportunities and the availability of credit.

In Columns 2 to 4 of Panel A in Table V we present the 2SLS results, which isolate the effect of weather-induced cash flow fluctuations on credit line draws. Columns 2 and 3 use the average daily abnormal snow cover in the first calendar quarter (*Abnormal Snow*) to instrument for annual cash flow. The coefficient estimates are -0.407 and -0.425, respectively, and are statistically significant. We find qualitatively similar second-stage estimates for the effect of cash flows on credit line use whether or not we include the time-varying firm controls, which is consistent with abnormal snow being unrelated to firm fundamentals. Column 4 shows that the 2SLS estimate is -0.524 and statistically significant when we use *Abnormal Snow* 95 as an IV for cash flow. These findings suggest that firms with access to bank debt cover approximately half of a weather related cash flow shock with credit line draws. This estimate is intuitive relative to the natural benchmark of -1.00, which would indicate that the firm managed the entire cash flow shock with credit line draws. In particular, Jiang (2017) highlights the need to anticipate the 2SLS magnitude and reconcile it with economic reality checks, particularly in cases such as ours where the 2SLS estimate is significantly larger in magnitude than the OLS estimate.[15]

These findings highlight the value of our two-stage procedure. By focusing on weather-induced variablity in cash flow, we identify the effect of cash flow changes on credit line draws in a manner that is not confounded by the high correlations between cash flows and other economic factors. Our results suggest that these correlations between cash flow and other factors are sufficiently strong to camouflage the extent to which credit lines are used

[15]See Section 3 of Jiang (2017). Another explanation for the larger 2SLS coefficient is that 2SLS identifies a local average treatment effect, where locality is determined by a firm's cash flow sensitivity to abnormally severe winter weather. Thus, the larger 2SLS coefficient could be because the firms that are most sensitive to our instrument (which Table 2 suggests are those in outdoor sectors or sectors that rely on an outdoor supply chain) happen to also have a larger sensitivity of credit line use to cash flows.

to buffer unanticipated, non-fundamental shocks to cash flow.

We conduct several additional robustness tests in Appendix Table AIV that offer circumstantial support for our identifying assumption that abnormally severe winter weather affects firm outcomes only through its effect on corporate cash flows. Column 1 replicates our analysis using a trimmed weather IV that drops the most extreme abnormal snow outcomes (i.e., the 8.5% of our sample that is more than three standard deviations away from the county's average over the past ten years). We obtain a very similar coefficient estimate of -0.562. Column 2 shows that our findings are also similar (with a point estimate of -0.448) after dropping areas that have experienced no snow over the previous decade. Taken together, these robustness analyses mitigate the concern that extreme weather events affecting investment opportunities or the population's expectations regarding future weather drive our findings.

Despite our outcomes of interest being measured as within-firm changes, it is possible that there are some time invariant firm characteristics that are related to both adverse winter weather and changes in credit line draw downs. We conduct a variety of analyses to mitigate the possibility that such time invariant firm characteristics drive our results. In Column 3 of Appendix Table AIV we control for such characteristics by adding firm fixed effects to our 2SLS specification. The point estimate for the effect of cash flows on credit line draw downs increases in size to -0.749, which is not consistent with the estimated effect in Column 3 of Table V being driven by time invariant firm characteristics. However, the inclusion of firm fixed effects results in the standard errors increasing almost four-fold (from 0.189 to 0.696) making the coefficient of interest statistically insignificant at conventional levels (with a t-statistic of approximately -1.1). This increase in standard errors is not surprising given that the inclusion of firm fixed effects reduces the degrees of freedom by approximately 52%.[16]

[16]Including firm fixed effects reduces the sample from 102,742, to 77,662 observations. In this smaller sample there are 28,892 firm fixed effects included in the regression leaving 48,762 degrees of freedom (compared to the 100,922 in the 2SLS specification in Column 3 of Table V).

In Panel B of Table V we present results of our reduced-form approach. Here, we regress credit line draws (scaled by the beginning of period total borrower loan commitments) directly on *Abnormal Snow*. In Columns 1 through 3 we continue to use a sample that requires financial statement information, as in the 2SLS analysis. Column 1 includes no firm-level controls or firm fixed effects (like Column 2 of Panel A), while Column 2 adds firm fixed effects (as in Column 3 of Appendix Table AIV) and Column 3 adds firm-level controls (as in Column 3 of Panel A). The statistical significance on these reduced form estimates is qualitatively similar to the 2SLS estimates in Panel A. In all three columns we find a positive relation between *Abnormal Snow* and credit line draw downs with the point estimates falling in a narrow band between 0.031 and 0.032. The similarity of the point estimates in Columns 1, 2, and 3 corroborate the evidence from Panel A that the relation between *Abnormal Snow* and credit line activity is orthogonal to the relation between firm characteristics and draw downs. Again, the point estimate becomes statistically insignificant in the smaller sample that includes firm fixed effects.

In Column 4 we conduct a similar analysis using an expanded sample that does not require financial statement information. This increases our sample size by approximately 87%, but the relation between *Abnormal Snow* and credit line draw downs remains similar with a highly statistically significant point estimate of 0.027. This is encouraging because it suggests that the relation between credit line activity and *Abnormal Snow* is not fundamentally different for the subset of borrowers for which we do not observe financial statement information.

In Column 5 we exploit the more complete panel used in Column 4 and add firm fixed effects. The coefficient does not change at all in magnitude and remains statistically significant at the 10% level, although the sample size decreases from 189,312 to 164,603. The similarity of the coefficients after the inclusion of firm fixed effects suggests that the relation between abnormal winter weather and credit line draws is not due to unobserved time-invariant firm-specific characteristics.

B. *Credit Line Size Adjustments*

Next, we investigate whether cash flow shocks cause firms to adjust their credit line size. Credit lines of public firms are frequently renegotiated — Roberts and Sufi (2009) and Roberts (2015) find that the average bank loan in their sample is renegotiated once every 6 to 9 months, and that most renegotiations are not due to impending covenant violations. Within our sample, credit line sizes are adjusted in almost half of firm-years. This raises the possibility that banks work with firms to adjust available credit in response to weather-induced cash flow shocks.

Interestingly, the OLS evidence in Column 1 of Table VI indicates the opposite relation. When cash flow is high, credit line size expands. This is consistent with profitable firms having greater demand for, or access to, bank credit. This is also consistent with Sufi (2009), who finds that the availability of credit lines can be dependent on maintaining high levels of cash flow, as lenders may use financial covenants to force loan renegotiation and reduce credit line availability following cash flow shortfalls (also see Smith (1993) and Smith and Warner (1979)).

Column 2 explores whether banks work with firms to manage non-fundamental liquidity shocks using IV regressions with the change in credit line size (scaled by beginning of period total assets) as the second stage dependent variable. The 2SLS results show a negative relation between exogenous cash flow shocks and credit line size. The coefficient of -0.526 indicates that a one dollar reduction in cash flow due to the weather shock is associated with an approximately 53 cent increase in end-of-year credit line size. Thus, although the OLS regressions show that general cash flow variability is positively associated with credit line size, the 2SLS results indicate that banks accommodate weather-induced cash flow shocks with credit line adjustments.

Appendix Table AV shows that these results are robust to using *Abnormal Snow* 95 to instrument for cash flows, dropping areas experiencing extremely large snow shocks, dropping areas that did not experience any snow in the previous decade, or removing the firm-level control variables. Across the first four columns of Appendix Table AV the coefficient of interest ranges from -0.495 to -0.841. Column 5 shows a coefficient of similar magnitude (-0.869) after including firm fixed effects. However, as in our analysis of credit line draws, including the firm fixed effects in our 2SLS framework substantially increases the standard errors (and reduces the degrees of freedom), leading to a statistically insignificant coefficient estimate.

In the last two columns of Table VI we use our reduced form specification and the larger sample that does not require financial statement information. In these specifications we scale the change in credit line size by total bank loan commitments as of the previous year (rather than total assets). Using this reduced form specification we find a significant negative relation between changes in credit line size and *Abnormal Snow*. The coefficient on *Abnormal Snow* is similar in magnitude and statistical significance whether or not firm fixed effects are included in the regression.

Together, the results in Tables V and VI indicate that bank-borrowing firms use their credit lines to manage non-fundamental liquidity shocks. Not only do these firms use existing credit line capacity when faced with weather-induced cash flow shocks, but they are also able to work with their lender to expand available credit. These adjustments are not apparent, even among bank-borrowing firms, without isolating the non-fundamental component of overall cash flow volatility.

We posit that the reason firms seek this additional credit is to maintain sufficient liquidity as they draw down their existing credit line. Consistent with this idea, we cannot reject the null hypothesis that the credit line drawdown (in Table V) is the same magnitude as the credit line size increase (in Table VI). Additionally, Table VII shows that the relation between *Abnormal Snow* and credit line draws and line size adjustments is concentrated in the sample of firms with low ex ante credit line slack. Focusing on firms with a credit line in place in the previous year, we partition firms into the *Low Slack* (*Slack*) group if the ratio of their unused-to-total credit line commitments at the beginning of the year is below (above) the

25^{th} percentile. Whether we include county- (Panel A) or firm-fixed effects (Panel B), there is a positive and statistically significant association between *Abnormal Snow* and credit line draws and line size changes only in the sub-sample of firms with *Low Slack*. These results help explain why the credit line size adjusts dollar for dollar with credit line draws - firms that draw on their line have limited excess credit line capacity.[17]

C. Other Liquidity Management Tools

The results presented thus far suggest that approximately half of every dollar of cash flow that a firm exogenously gains (or loses) is reflected in a change in the end-of-year credit line balance. In the next set of tests, we examine whether firms manage the remainder of the exogenous cash flow shock along other dimensions that we can observe. Specifically, we test the relation between weather-induced cash flow shocks and annual changes in cash balances, fixed assets, trade credit, and total debt. A limitation to our study is that we do not observe an exhaustive list of the potential liquidity buffers available to firms, such as reducing corporate payouts, increasing equity issuance, using financial hedges, or cutting costs (in forms unrelated to operating cash flows).

Column 1 of Table VIII presents 2SLS estimates where the second stage dependent variable is the annual change in cash balance, scaled by beginning of year total assets. Although the relation between weather-induced cash flow shocks and changes in end-of-year cash balances is not significant at conventional levels (with a t-statistic of approximately 1.5), the point estimate of 0.18 suggests that 18 cents of every dollar lost due to weather-induced cash flows manifests as a reduction in the end-of-year cash balance. In Column 2 we find that the liquidity buffers at firms' disposal are sufficient to prevent weather-induced cash flow shocks from significantly affecting real activities (measured as a change in fixed assets).

[17] One explanation for these results is that firms that use credit lines to manage weather-induced cash flow shocks also actively use their credit lines in response to other liquidity shocks, whereas firms with ample credit line slack have credit lines in place for investment purposes, such as mergers and acquisitions.

Several studies show that trade credit is another way firms can manage liquidity shocks (see e.g., Petersen and Rajan (1997), Giannetti et al. (2011), Garcia-Appendini and Montoriol-Garriga (2013), and Shenoy and Williams (2017)). We examine this possibility in Column 3, but find little evidence of a relation between cash flow shocks and changes in net trade credit. For the analysis presented in Column 3 we measure trade credit as accounts receivable minus accounts payable divided by lagged sales. We continue to find no significant relation between weather-induced cash flows and trade credit if we focus separately on accounts receivable or accounts payable, or if we scale by lagged total assets instead of total sales. Although these proxies are similar to the measures used in the literature (see e.g., Murfin and Njoroge (2014), Barrot (2016), and Chod et al. (2019)), we cannot rule out measurement error in our proxies for trade credit as a possible explanation for the null results. Another likely explanation for the lack of an important trade credit effect is that the data is only available at an annual frequency, and any trade credit that is extended to address the cash flow shock is repaid within the year. In unreported tests, we also find no significant changes in non-cash working capital, which includes net trade credit as well as other line items, such as inventories.

Finally, in Column 4 we show that the effect of weather-induced cash flow shocks on the year-over-year change in total debt is very similar to the the credit line draw effect we document in Table V. This implies that credit line draws represent the vast majority of the increase in total debt in response to weather-induced cash flow shocks.

Overall, the point estimates in Tables V and VIII suggest that for every dollar an exogenous cash flow shock costs a firm, approximately 50 cents is reflected in increased credit line draws, and approximately 18 cents is reflected in reduced cash by the end of the year. Thus, credit lines are an important tool firms use to manage exogenous cash flow shocks, although it remains likely that firms manage a portion of exogenous cash flow shocks in other less observable ways.

D. *Quarterly Credit Line Adjustments*

Until this point, we have focused on end-of-year outcomes, which represent two to four quarter liquidity buffers. Although we do not observe quarterly financial statements, we do observe quarterly credit line activity. Thus, we can use our reduced-form analysis to examine the relation between severe first quarter snow and credit line activity on a quarterly basis. In Figure 2 we decompose the annual effect of *Abnormal Snow* on the change in credit line drawn amount into its quarterly components. The figure is estimated from four regressions, one for each calendar quarter. Each regression regresses changes in credit line activity between the end of the previous year and the end of the calendar quarter denoted on the x-axis on *Abnormal Snow*. Thus, the estimates are cumulative within the calendar year (i.e., moving from left to right on the figure), since they each represent changes in credit line activity since the previous year end.

The solid line in Panel A presents the point estimate for the current year's *Abnormal Snow*, and the short dashed lines present the 95% confidence intervals on this estimate. Panel B presents corresponding estimates using the following (instead of the current) year's *Abnormal Snow*. Since the following year's *Abnormal Snow* has yet to occur at the time the credit line activity is measured, Panel B is a placebo test under our identifying assumption that bank borrowers do not anticipate impending *Abnormal Snow*.

Panel A of Figure 2 shows that the effect of abnormal first quarter snow on credit line draws is concentrated in the first and second second calendar quarters. This finding indicates that firms respond to bad weather between January 1 and March 31 by drawing on their credit line at some point between January 1 and June 30th. The majority of the effect occurs between the end of the first and second quarters. Because the points on the line estimate cumulative credit line draws since the end of the previous year, the flattening of the line after quarter 2 suggests that credit line draws in the second half of the year are unrelated to first quarter abnormal snow cover. In addition, the small magnitude and statistical insignificance of the relation between current year's credit line draws and future abnormal snow cover suggested in Panel B further bolsters our identifying assumption that borrowers do not adjust their corporate policies in anticipation of future adverse weather shocks.

Figure 3 conducts a similar analysis using cumulative changes in credit line size as the outcome of interest. The results here are qualitatively similar to those in Figure 2, except that line size adjustments occur with a slightly longer lag as they are concentrated almost exclusively in the second quarter. The point estimates in Figure 3 are approximately twice as large, but statistically similar to those in Figure 2. Again, Panel B indicates no evidence that line size changes in the second half of the current year or any point in the previous year are related to first quarter abnormal snow.

Taken together, the evidence in Figures 2 and 3 are consistent with banks providing liquidity to firms experiencing exogenous cash flow shocks. Firms draw on their credit line during the quarter of and following the shock, and then work with their bank to increase credit line size within approximately three months of the shock.

V. Effect on Loan Contract Terms

The likely mechanism through which borrowers' credit line limits increase in response to weather-induced cash flow shocks is loan renegotiation between the borrower and the lender. Renegotiation in this case could either be initiated by borrowers or forced by lenders as a result of financial covenant violations. Given the line size increase we observe, it is likely that a large portion of the weather-induced renegotiations in our sample are borrower initiated.[18] Although a lack of data on loan covenants precludes a direct examination of the type of loan renegotiations in our sample, our data allow us to examine how weather-induced cash flow shocks shape the loan contract along other key dimensions.

If managing non-fundamental cash flow shocks is an economically important use of credit

[18]For example, Roberts and Sufi (2009) provide descriptive evidence that only approximately 3% to 4% of renegotiations that lead to loan amount increases experience covenant violations in the previous or the current year.

lines, then banks are likely to charge borrowers for this service. The most direct way that banks charge borrowers is via interest rate increases during the renegotiation process, however banks may also indirectly charge borrowers by adjusting other loan terms (e.g., keeping interest rates constant, but shorten the maturity of the loan). We investigate these empirical questions by examining the relation between weather-induced cash flow shocks and a variety of loan contract terms.

We begin by examining the relation between cash flows and interest rates charged both on credit lines and on all loans to a given borrower. Investigating all loans gives a more complete picture of how the cost of credit changes as the borrower and lender are likely to simultaneously renegotiate all credit facilities. In Panel A of Table IX the dependent variable is the change in the (value weighted) average interest rate a borrower pays on their credit lines over the course of the year. Column 1 of Table IX presents 2SLS estimates for the relation between weather-induced cash flows and interest rate changes. We find that weather-induced cash flow changes have a significant negative relation with the interest rates charged on bank lines of credit. The coefficient estimate of -0.051 suggests that when cash flow falls by 1% of a firm's beginning of period total assets, interest rates increase by approximately 5 basis points. Thus, banks appear to charge borrowers for the liquidity they use to buffer cash flow shocks, even when those shocks are orthogonal to firm fundamentals. This effect is approximately 2 basis points in column 2 when we expand the sample to all loans of a given borrower. This implies the pricing effect of exogenous cash flow shocks is essentially zero within non-credit line bank loans.

A limitation to our data is that we do not observe the interest on undrawn lines of credit. Thus, our sample of borrower-years with reported financial information includes only 40,959 borrower-years (i.e., those that have drawn credit lines at the end of both the current and previous year). Expanding the sample to include borrower-years without complete financial statement information more than doubles the observations to 91,529 borrower-years. Columns 3 and 4 qualitatively support the idea that banks charge for the liquidity they provide to firms in response to weather-induced cash flow shocks using our reduced form approach and the larger sample. We find a significant positive relation between interest rate changes and *Abnormal Snow* in Column 3, which includes county and industry x year-quarter fixed effects. Column 4 shows that this relation persists, and is approximately 50% larger, after the inclusion of firm fixed effects. Columns 5 and 6 show that these results are very similar when we expand the sample to all the loans of a given borrower.

There are also a variety of non-price loan terms that banks may adjust in response to weather-induced cash flow shocks. Our data allow us to analyze some, but not all, of these potential adjustments. To maximize sample size, in the remainder of the analysis we examine changes in the average contract terms of all the loans of a given borrower.[19] Specifically, in Panels A through C of Table X we examine the loan maturity, the probability of a fixed (as opposed to variable) interest rate contract, and the probability that a loan is secured by accounts receivable or inventory.

Panels A through C of Table X suggest that weather-induced cash flow shocks lead to less borrower-friendly non-price loan terms. Column 1 presents 2SLS estimates indicating that when weather negatively impacts cash flow, loans become shorter in maturity, less likely to have fixed interest rates, and are more likely to be secured by accounts receivable or inventory. Columns 2 and 3 corroborate these results using our reduced form approach, with and without firm fixed effects. All coefficients are statistically significant at the 5% level or better, although the standard errors do consistently increase after the inclusion of firm fixed effects.

The evidence in this section suggests that banks charge borrowers for the liquidity they provide in response to non-fundamental cash flow shocks. They charge borrowers through a combination of higher interest rates and less favorable non-price loan terms. The fact that borrowers are willing to pay along these dimensions supports the idea that an important role

[19]Unreported tests show that results are very similar if we consider the contract terms of only the lines of credit of a given borrower.

of credit lines is to help firms manage non-fundamental liquidity shocks.

VI. Heterogeneity

In our final set of tests we examine whether certain types of firms are more or less likely to use credit lines to manage weather-induced cash flow shocks. These tests should be interpreted descriptively as they entail endogenous partitions of the data. Moreover, these partitions weaken the statistical significance of our IV.[20] Accordingly, we focus primarily on our reduced-form analyses.

We begin by partitioning our sample based on firm size. Specifically, in Panel A of Table XI we partition the sample based on whether the borrower has over $100 million in total assets. We treat firms that do not report total assets as having less than $100 million in total assets, however results are qualitatively similar excluding those firms from the analysis.[21] The results suggest that small firms rely more heavily on credit lines to manage weather-induced cash flow shocks.[22] There is a statistically significant positive relation between *Abnormal Snow* and both credit line draws (Columns 1 and 2) and changes in credit line size (Columns 5 and 6) among the 80% of firms with less than $100 million in total assets. We find no significant relation between *Abnormal Snow* and either credit line outcome for firms with over $100 million in total assets. Moreover, the coefficients in Columns 3 and 4 suggest that this does not appear to be due to a lack of statistical power as the coefficients are not only statistically insignificant, but also smaller in magnitude.

[20]In most specifications *Abnormal Snow* still significantly negatively predicts annual cash flows, but its t-statistic is often below traditional weak instrument thresholds.

[21]Results are also qualitatively similar partitioning on $50 million or $75 million in total assets or $100 million in sales.

[22]More broadly, these findings suggest that credit lines play a first-order role in helping small firms manage any non-fundamental variability in corporate cash flows. This relates to the broader literature examining the effects of non-fundamental cash flow shocks on larger public firms (e.g., Rauh (2006), Bakke and Whited (2012), Dambra (2017), Blouin and Krull (2009), Faulkender and Petersen (2012)).

These findings suggest that the use of credit lines to buffer weather-induced cash flow shocks is most common among small borrowers. In Appendix Table AVI we replicate the results from Panel A of Table XI with change in cash holdings as the dependent variable. Within the subsample of large firms, there is a negative and statistically significant association between *Abnormal Snow* and changes in cash. This evidence is consistent with larger firms using cash, as opposed to credit lines, as a solution to weather-induced cash flow shocks. Appendix Table AVII corroborates the tenor of this result using our 2SLS procedure. Small firms make approximately dollar for dollar draws and adjustments on their credit lines in response to cash flow shocks, and do not significantly adjust their cash balances. In contrast, large firms manage approximately 38% of the cash flow shock by adjusting year-end cash balances, but do not significantly adjust their credit lines. These findings raise the possibility that larger firms manage parts of non-fundamental cash flow shocks in ways that we do not observe in the data such as reduced equity payouts, increased equity issuances, or financial hedges. An important consideration when interpreting these results is that there are multiple reasons why small firms may exhibit an increased propensity to manage weather-induced cash flow shocks with credit lines, including lower diversification across geography and industry and more difficulty accessing capital markets to issue new equity or use financial hedges.

Panel B of Table XI shows that the use of credit lines to manage weather-induced cash flows shocks is also concentrated in firms with close proximity to their lenders. Specifically, we find no evidence that firms in our sample that are headquartered more than 100 miles away from the nearest syndicated lending office of their lead bank use credit lines to buffer weather-induced cash flow shocks. However, this result should not be interpreted causally because, in addition to being correlated with a variety of observable firm characteristics, a borrower's choice to be geographically close to their lender may be related to credit line use.

Finally, in Panel C we partition the sample on the borrower's credit quality. We find that the use of credit lines to manage non-fundamental cash flow shocks is concentrated in the approximately 82% of borrower-years with credit ratings of BB or higher.[23] For instance, Column 1 shows that the estimated relation between credit line drawdowns and *Abnormal Snow* is 0.032 among the 153,667 borrower-years rated BB or better and 0.007 among the 34,133 borrower-years rated B or worse.[24] The remaining columns paint a similar picture. These findings suggest that the lowest credit quality borrowers are not able to use credit lines to manage exogenous liquidity shocks. This result is consistent with theory. For example, Diamond (1991) argues that low- and medium-credit risk borrowers can rely on bank financing for liquidity, but high credit risk borrowers may not be able to do so, even when facing non-fundamental liquidity shocks.

VII. Concluding Remarks

This study uses a unique dataset on bank lending portfolios to study how firms manage liquidity in the face of non-fundamental cash flow shocks. Starting in 2012, the Federal Reserve has collected comprehensive data on bank lending activities as part of the Dodd-Frank Stress Tests and Comprehensive Capital Analysis and Review. The resulting data (the Federal Reserve Y-14 collection) contains a rich dataset on bank loans to small, mid-sized, and large companies in the United States. Notably, the FR Y-14 Collection has broad coverage of loan terms and financial statements of the small private firms that rely extensively on external credit, but typically do not appear in publicly available databases.

We show that these firms rely extensively on credit lines as a source of external finance. To identify a causal link between cash flow shocks and corporate liquidity management, we

[23]As a sanity check, in unreported tests we find that within the 2SLS sample low credit quality borrowers (as defined by the internal bank rating) have future probabilities of default of greater than 6.4% (as estimated by the lender) as compared to high credit quality borrowers that have a probability of default of only 0.7%. Within the full reduced form sample low credit quality borrowers have a probability of default of 5.4% versus 1.1% probability of default of high credit quality borrowers.

[24]In unreported tests we verify that the average weather shocks are nearly identical in size between the two subsamples. Additionally, the t-stat for differences in means indicates a lack of statistical difference.

construct an instrument for cash flow based on abnormal adverse winter weather conditions in the county in which the company is located. Using this instrument to predict firm-level cash flows, we find that firms manage negative cash flow shocks primarily by drawing on their credit lines rather than tapping cash reserves or adjusting real activities. Negative cash flow shocks are also accompanied by significant increases in the size of the firm's overall credit line, indicating that banks accommodate borrowers faced with unexpected cash flow shortfalls. These credit line adjustments occur within one calendar quarter and persist through the end of the year. Additional tests show that banks charge borrowers for this liquidity provision via increased interest rates and less borrower-friendly loan provisions. Specifically, we find that weather-induced cash flow shocks lead to higher interest rates, shorter loan maturity, and an increased probability of the loan being secured or having a variable interest rate.

One important qualification is that our results are driven by small firms and cannot be extrapolated to the large public (e.g., COMPUSTAT) firms that researchers often study. Whereas larger firms tend to rely more on cash holdings to manage liquidity, the main takeaway from our work is that one important function of bank credit lines is to buffer liquidity shocks experienced by smaller solvent firms.

REFERENCES

Acharya, Viral, Heitor Almeida, and Murillo Campello, 2013, Aggregate risk and the choice between cash and lines of credit., *Journal of Finance* 68, 2059–2116.

Acharya, Viral, Heitor Almeida, Filippo Ippolito, and Ander Perez, 2014, Credit lines as monitored liquidity insurance: Theory and evidence, *Journal of Financial Economics* 112, 287–319.

Almeida, Heitor, Murillo Campello, Igor Cunha, and Michael Weisbach, 2014, Corporate liquidity management: A conceptual framework and survey, *Annual Review of Financial Economics* 6, 135–162.

Almeida, Heitor, Murillo Campello, and Michael Weisbach, 2004, The cash flow sensitivity of cash., *Journal of Finance* 59, 1777–1804.

Bakke, Tor-Erik, and Toni M Whited, 2012, Threshold events and identification: A study of cash shortfalls, *The Journal of Finance* 67, 1083–1111.

Barrot, Jean-Noel, 2016, Trade credit and industry dynamics: Evidence from trucking firms, *The Journal of Finance* 71, 1975–2016.

Bates, Thomas W., Kathleen M. Kahle, and Renee M. Stulz, 2009, Why do u.s. firms hold so much more cash than they used to?, *Journal of Finance* 64, 1985–2021.

Berger, Allen N, Nathan H Miller, Mitchell A Petersen, Raghuram G Rajan, and Jeremy C Stein, 2005, Does function follow organizational form? evidence from the lending practices of large and small banks, *Journal of Financial economics* 76, 237–269.

Berger, Allen N, and Gregory F Udell, 1995, Relationship lending and lines of credit in small firm finance, *Journal of business* 351–381.

Berospide, Jose, and Ralf Meisenzahl, 2016, The real effects of credit line drawdowns, Working Paper.

Bidder, Rhys M., John R. Krainer, and Adam H. Shapiro, 2016, Drilling into bank balance sheets: Examining portfolio responses to an oil shock, Working Paper.

Blackwell, David W, and Drew B Winters, 1997, Banking relationships and the effect of monitoring on loan pricing, *Journal of Financial Research* 20, 275–289.

Bloesch, Justin, and Francois Gourio, 2015, The effect of winter weather on u.s. economic activity., *Economic Perspectives, FRB Chicago.*

Blouin, Jennifer, and Linda Krull, 2009, Bringing it home: A study of the incentives surrounding the repatriation of foreign earnings under the american jobs creation act of 2004, *Journal of Accounting Research* 47, 1027–1059.

Cachon, Gerard P., Santiago Gallino, and Marcelo Olivares, 2012, Severe weather and automobile assembly productivity, Working Paper.

Campello, Murillo, Erasmo Giambona, John Graham, and Campbell Harvey, 2011, Liquidity management and corporate investment during a financial crisis., *Review of Financial Studies* 24, 1944–1979.

Campello, Murillo, Erasmo Giambona, John Graham, and Campbell Harvey, 2012, Access to liquidity and corporate investment in europe during the financial crisis., *Review of Finance* 16, 323–346.

Chen, Yangyang, Po-Hsuan Hsu, Edward J. Podolski, and Madhu Veeraraghavan, 2017, In the mood for creativity: Weather-induced mood, inventor productivity, and firm value, Working Paper.

Chod, Jiri, Evgeny Lyandres, and S Alex Yang, 2019, Trade credit and supplier competition, *Journal of Financial Economics* 131, 484–505.

Cortes, Kristle Romero, 2014, Rebuilding after disaster strikes: How local lenders aid in the recovery, FRB of Cleveland Working Paper No. 14-28.

Cortes, Kristle Romero, and Philip E. Strahan, 2016, Tracing out capital flows: How financially integrated banks respond to natural disasters, *Journal of Financial Economics* forthcoming.

Dambra, Michael J, 2017, Stakeholder conflicts and cash flow shocks: Evidence from changes in erisa pension funding rules, *The Accounting Review* 93, 131–159.

Demiroglu, Cem, and Christopher James, 2011, The use of bank lines of credit in corporate liquidity management: A review of empirical evidence., *Journal of Banking and Finance* 35, 775–782.

Demiroglu, Cem, Christopher James, and Atay Kizilaslan, 2012, Bank lending standards and access to lines of credit., *Journal of Money, Credit and Banking* 44, 1063–1089.

Denis, David, and Valeriy Sibilkov, 2010, Financial constraints, investment, and the value of cash holdings., *Review of Financial Studies* 23, 247–269.

Dessaint, Olivier, and Adrien Matray, 2017, Do managers overreact to salient risks? evidence from hurricane strikes, *Journal of Financial Economics* 126, 97–121.

Diamond, Douglas, 1991, Monitoring and reputation: The choice between bank loans and directly placed debt., *Journal of Political Economy* 99, 689–721.

Faulkender, Michael, and Mitchell Petersen, 2012, Investment and capital constraints: repatriations under the american jobs creation act, *The Review of Financial Studies* 25, 3351–3388.

Fuss, Catherine, and Philip Vermeulen, 2008, The response of firms' investment and financing to adverse cash flow shocks: the role of bank relationships in belgium, *Review of Business and Economics* 1, 5–34.

Garcia-Appendini, Emilia, and Judit Montoriol-Garriga, 2013, Firms as liquidity providers: Evidence from the 2007–2008 financial crisis, *Journal of financial economics* 109, 272–291.

Gatev, Evan, and Phillip Strahan, 2006, Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market., *Journal of Finance* 61, 867–892.

Giannetti, Mariassunta, Mike Burkart, and Tore Ellingsen, 2011, What you sell is what you lend? explaining trade credit contracts, *The Review of Financial Studies* 24, 1261–1298.

Giroud, Xavier, Holger M. Mueller, Alex Stomper, and Arne Westerkamp, 2012, Snow and leverage, *Review of Financial Studies* 25, 680–710.

Gustafson, Matthew, Ivan Ivanov, and Ralf Meisenzahl, 2019, Bank monitoring: Evidence from syndicated loans, Working Paper.

Holmstrom, Bengt, and Jean Tirole, 1998, Private and public supply of liquidity, *Journal of Political Economy* 106, 1–40.

Houston, Joel F, and Christopher M James, 2001, Do relationships have limits? banking relationships, financial constraints, and investment, *The Journal of Business* 74, 347–374.

Ivashina, Victoria, and David Scharfstein, 2010, Bank lending during the financial crisis of 2008, *Journal of Financial Economics* 97, 319–338.

James, Christopher, and Peggy Wier, 1990, Borrowing relationships, intermediation, and the cost of issuing public securities, *Journal of Financial Economics* 28, 149–171.

Jiang, Wei, 2017, Have instrumental variables brought us closer to the truth, *The Review of Corporate Finance Studies* 6, 127–140.

Jimenez, Gabriel, Jose Lopez, and Jesus Saurina, 2009, Empirical analysis of corporate credit lines., *The Review of Financial Studies* 22, 5069–5098.

Kashyap, Anil, Raghuram Rajan, and Jeremy Stein, 2002, Banks as liquidity providers: An explanation for the co-existence of lending and deposit-taking., *Journal of Finance* 57, 33–37.

Koetter, Michael, Felix Noth, and Oliver Rehbein, 2019, Borrowers under water! rare disasters, regional banks, and recovery lending, *Journal of Financial Intermediation* .

Lins, Karl, Henry Servaes, and Peter Tufano, 2010, What drives corporate liquidity? an international survey of cash holdings and lines of credit., *Journal of Financial Economics* 98, 160–176.

Murfin, Justin, and Ken Njoroge, 2014, The implicit costs of trade credit borrowing by large firms, *The Review of Financial Studies* 28, 112–145.

Ongena, Steven, and David C Smith, 2001, The duration of bank relationships, *Journal of financial economics* 61, 449–475.

Petersen, Mitchell A., and Raghuram G. Rajan, 1994, The benefits of lending relationships: Evidence from small business data, *Journal of Finance* 49, 3–37.

Petersen, Mitchell A, and Raghuram G Rajan, 1995, The effect of credit market competition on lending relationships, *The Quarterly Journal of Economics* 110, 407–443.

Petersen, Mitchell A, and Raghuram G Rajan, 1997, Trade credit: theories and evidence, *The Review of Financial Studies* 10, 661–691.

Petersen, Mitchell A, and Raghuram G Rajan, 2002, Does distance still matter? the information revolution in small business lending, *The journal of Finance* 57, 2533–2570.

Rauh, Joshua D, 2006, Investment and financing constraints: Evidence from the funding of corporate pension plans, *The Journal of Finance* 61, 33–71.

Robb, Alicia, and David T. Robinson, 2014, The capital structure decisions of new firms., *Review of Financial Studies* 27, 153–179.

Roberts, Michael R., 2015, The role of dynamic renegotiation and asymmetric information in financial contracting., *Journal of Financial Economics* 116, 61–81.

Roberts, Michael R., and Amir Sufi, 2009, Renegotiation of financial contracts: Evidence from private credit agreements., *Journal of Financial Economics* 93, 159–184.

Shenoy, Jaideep, and Ryan Williams, 2017, Trade credit and the joint effects of supplier and customer financial characteristics, *Journal of Financial Intermediation* 29, 68–80.

Shockley, Richard, and Anjan Thakor, 1997, Bank loan commitment contracts: Data, theory and tests., *Journal of Money, Credit and Banking* 29, 517–534.

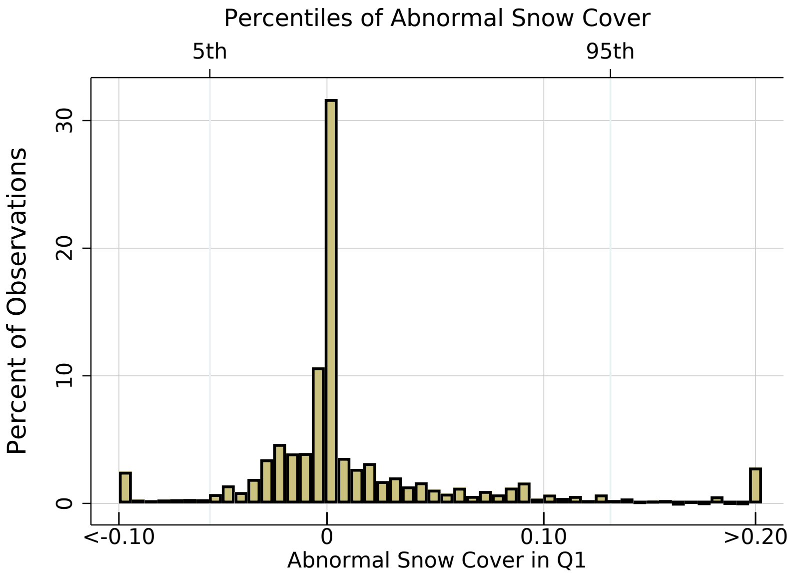
Smith, Jr., Clifford W., 1993, A perspective on accounting-based debt covenant violations, *The Accounting Review* 68, 289–303.

Smith, Jr., Clifford W., and Jerold B. Warner, 1979, On financial contracting, *Journal of Financial Economics* 7, 117–161.

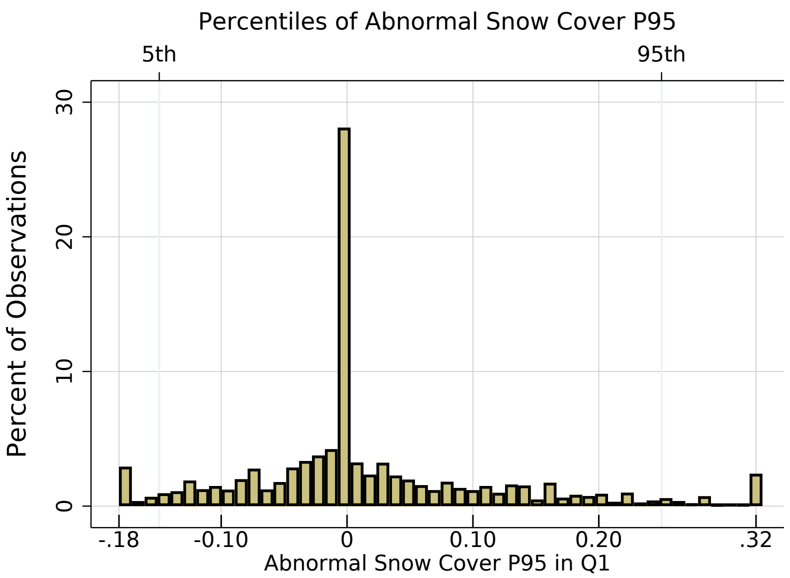
Stock, James, and Motohiro Yogo, 2005, Testing for weak instruments in linear iv regressions., *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*.

Sufi, Amir, 2009, Bank lines of credit in corporate finance: An empirical analysis., *Review of Financial Studies* 22, 1057–1088.

Yun, Hayong, 2009, The choice of corporate liquidity and corporate governance., *Review of Financial Studies* 22, 1447–1475.

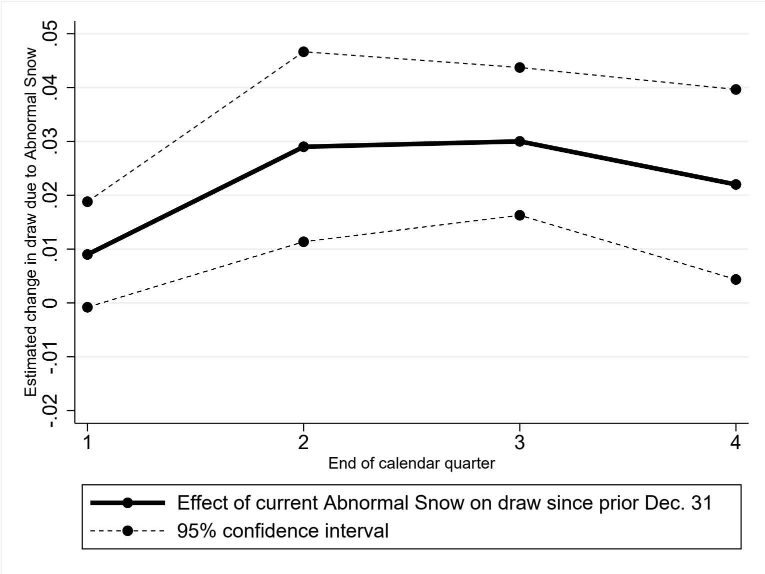


(a) *Abormal Snow Cover*

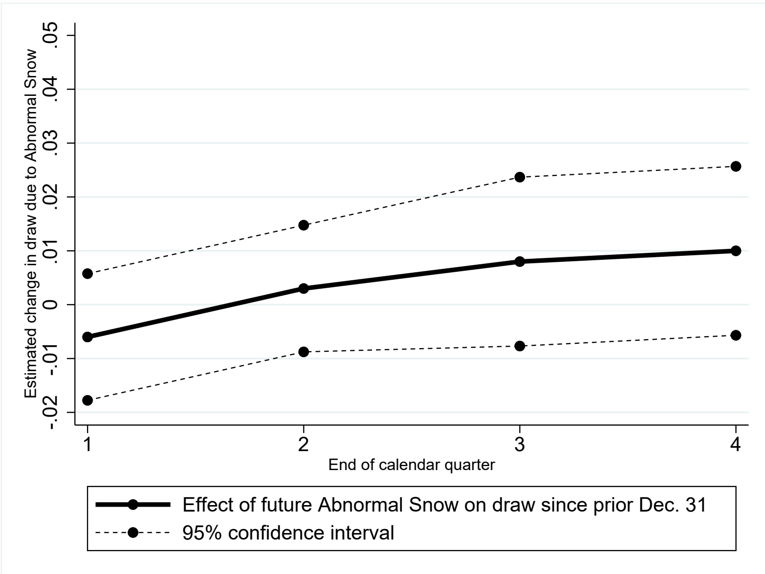


(b) *Abnormal Snow Cover P95*

Figure 1: Distribution of Abnormal Snow Cover. This figure presents the distribution of abnormal snow cover during the first calendar quarter for the 102,742 firm-years in our 2SLS sample. The distribution in Panel A is constructed based on the average daily snow cover during the first calendar quarter, while Panel B uses the 95th percentile of snow cover during the first calendar quarter. Abnormal snow cover is defined relative to the time-series average of first calendar quarter snow cover in each county over the previous 10 years.

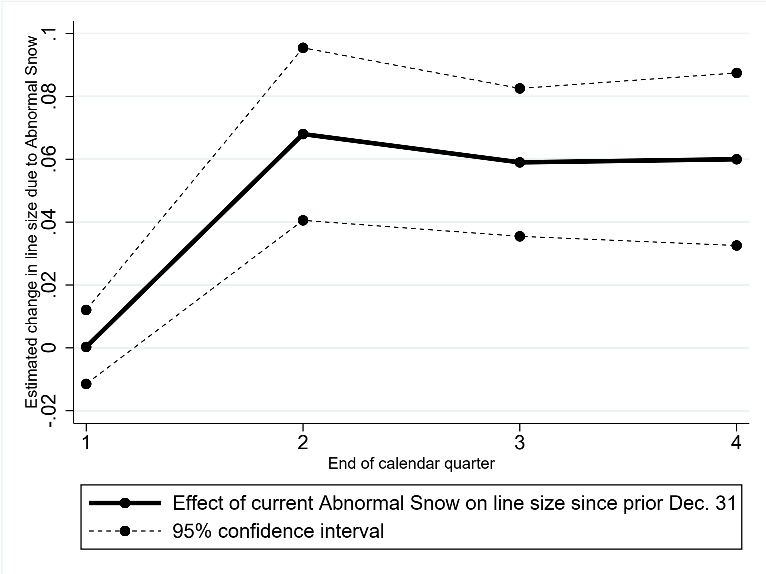


(a) Line Draw and Current Year's Abnormal Snow

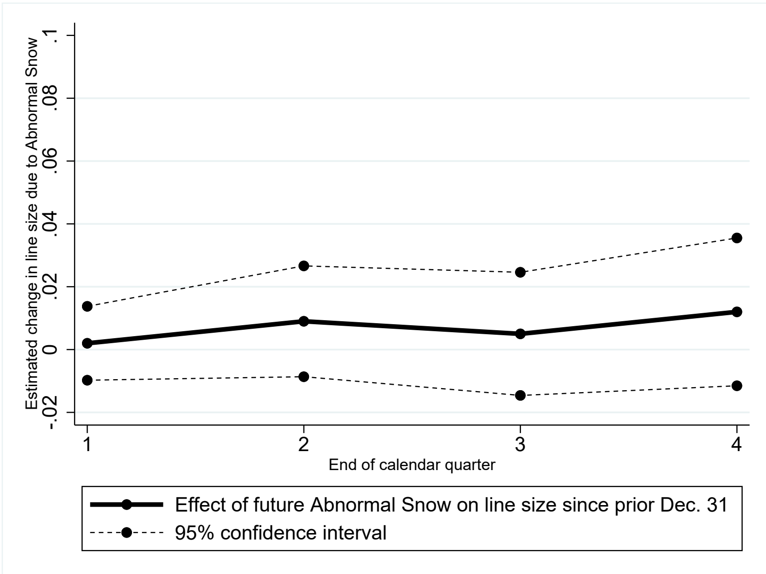


(b) Line Draw and Next Year's Abnormal Snow

Figure 2: Quarterly Credit Line Draw and Abnormal Snow. This figure presents the relation between the current (Panel A) and future (Panel B) year's *Abormal Snow* and quarterly credit line draw activity. The figure is estimated from four regressions, one for each calendar quarter. The point estimates (i.e., the solid line) reflect the cumulative effect of *Abormal Snow* on credit line drawdowns from the end of the previous year until the end of the calendar quarter denoted on the x-axis. Specifically, each regression regresses changes in credit line activity between December 31 of the previous year and the end of the calendar quarter denoted on the x-axis on *Abormal Snow* in both the current and the following year. The solid line presents the point estimates for *Abormal Snow* in the current year (Panel A) and in the following year (Panel B). The short dashed lines present the 95 percent confidence intervals on this estimate.



(a) Line Size and Current Year's Abnormal Snow



(b) Line Size and Next Year's Abnormal Snow

Figure 3: Quarterly Credit Line Size and Abnormal Snow. This figure presents the relation between the current (Panel A) and future (Panel B) year's *Abormal Snow* and quarterly credit line size changes. The figure is estimated from four regressions, one for each calendar quarter. The point estimates (i.e., the solid line) reflect the cumulative effect of *Abormal Snow* on credit line drawdowns from the end of the previous year until the end of the calendar quarter denoted on the x-axis. Specifically, each regression regresses changes in credit line activity between December 31 of the previous year and the end of the calendar quarter denoted on the x-axis on *Abormal Snow* in both the current and the following year. The solid line presents the point estimates for *Abormal Snow* in the current year (Panel A) and in the following year (Panel B). The short dashed lines present the 95 percent confidence intervals on this estimate.

Table I: Descriptive Statistics. This table presents descriptive statistics for our sample of 102,742 firm-years with available borrower and loan characteristics. All variables with the exception of *Total Assets* are scaled by firm total assets as of the previous year. Columns 1 and 2 present the mean and standard deviation, while Columns 3 through 5 present the 25th, 50th, and 75th percentiles, respectively. The *Line Size* statistics use a smaller sample of the 64,983 firm-years with available credit lines. All explanatory variables are defined in Appendix B.

	Mean	*SD*	*P25*	*P50*	*P75*
Total Assets ($ Millions)	706.92	3021.84	7.98	21.34	92.64
Cash Flow	0.16	0.21	0.06	0.12	0.20
Leverage	0.61	0.21	0.47	0.63	0.77
Fixed Assets	0.29	0.27	0.06	0.20	0.45
Sales	2.31	1.94	1.06	1.96	3.03
Cash	0.10	0.13	0.01	0.05	0.14
Debt	0.32	0.24	0.12	0.29	0.48
WorkCap	0.10	0.21	−0.03	0.07	0.22
Line Size	0.24	0.19	0.09	0.20	0.35
Δ *Line Size*	0.03	0.12	0.00	0.00	0.01
Draw	0.09	0.15	0.00	0.00	0.12
Δ *Drawn*	0.02	0.10	0.00	0.00	0.01

Table II: Cash Flow and Abnormal Weather. This table contains estimated coefficients from an OLS regression of $Cash\ Flow_{it}$ on *Abnormal Snow* (columns 1 and 2) and *Abnormal Snow P*95 (columns 3 and 4). All columns include four-digit NAICS industry x year-quarter fixed effects and county fixed effects. The standard errors are clustered at the four-digit NAICS 2012 industry level. All variables are defined in Appendix B.

	$Cash\ Flow_{it}$			
	(1)	(2)	(3)	(4)
Abn. Snow	−0.029***	−0.028***		
	(0.006)	(0.006)		
*Abn. Snow P*95			−0.019***	−0.017***
			(0.004)	(0.004)
$Log(Assets_{it-1})$		−0.003*		−0.003*
		(0.001)		(0.001)
$Fixed\ Assets_{it-1}$		0.093***		0.093***
		(0.013)		(0.013)
$Leverage_{it-1}$		−0.078***		−0.078***
		(0.021)		(0.0321)
$Sales_{it-1}$		0.034***		0.034***
		(0.004)		(0.004)
$Cash_{it-1}$		0.222***		0.222***
		(0.035)		(0.035)
$Debt_{it-1}$		0.003		0.003
		(0.024)		(0.024)
$WorkCap_{it-1}$		0.023***		0.023***
		(0.008)		(0.008)
Industry x Year-quarter FEs	YES	YES	YES	YES
County Fixed Effects	YES	YES	YES	YES
Adjusted R-Squared	0.139	0.235	0.139	0.235
Observations	102,742	102,742	102,742	102,742

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table III: Cash Flow and Abnormal Weather: Industry Partitions This table contains estimated coefficients from an OLS regression of *Cash Flow*$_{it}$ on *Abnormal Snow*. Each row in the table restricts the sample to the sector indicated in Column 1. Columns 2 and 3 present the estimates (and standard errors below in parentheses) for the coefficients on *Abnormal Snow* and *Abnormal Snow P*95, respectively. We include identical controls to those in Specification (2) of Table II (defined in Appendix B), as well as state and year fixed effects. The standard errors are adjusted for heteroskedasticity. Borrower industry is defined in terms of the 2-digit NAICS code corresponding to each borrower. Borrowers with 2-digit NAICS codes of 31, 32, and 33 are classified as "Manufacturing"; 42 is classified as "Wholesale Trade"; 44 and 45 as "Retail Trade"; 48 and 49 as "Transportation"; 53 as "Real Estate"; 54, 55, and 56 as "Business Services"; 61 and 62 as "Education & Health"; 23 as "Construction'.

All unreported industries comprise less than 4% of our sample, observations total 103,265.

	Ab. Snow (*SE*)	Ab. Snow P95 (*SE*)	% *Obs*	*Obs*
MANUFACTURING	−0.027**	−0.012	23.6%	24,370
	(0.013)	(0.008)		
WHOLESALE	−0.015	−0.014**	17.4%	17,927
	(0.012)	(0.007)		
RETAIL	−0.022*	−0.015*	14.1%	14,509
	(0.013)	(0.008)		
BUSINESS SERVICES	−0.053	−0.016	9.5%	9,778
	(0.037)	(0.022)		
REAL ESTATE	−0.082***	−0.056***	7.5%	7,729
	(0.026)	(0.015)		
CONSTRUCTION	−0.041**	−0.020**	7.1%	7,320
	(0.018)	(0.010)		
EDUCATION & HEALTH	−0.036	−0.010	4.6%	4,733
	(0.074)	(0.043)		
TRANSPORTATION	−0.059*	−0.037**	4.1%	4,217
	(0.032)	(0.018)		

Standard errors in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table IV: Descriptive Statistics, Partitioned by Weather Shock. This table presents descriptive statistics for our sample of 102,742 observations with available borrower and loan characteristics. The sample is partitioned by *Abnormal Snow* tercile, with sample sizes ranging from 33,854 (tercile 1) to 34,908 (tercile 3). Columns 1 and 2 present the mean and median for the first tercile of *Abnormal Snow*, while Columns 3 and 4 (5 and 6) do the same for the second (third) tercile. Column 7 presents the difference between the averages in the first and third terclie using linear regressions. The regressions include county and industry-year-quarter fixed effects and the standard errors are clustered at the 4 digit NAICS code level. *, **, *** represent significant differences at the 10%, 5%, and 1% levels after absorbing county and industry-year-quarter variation and clustering at the 4-digit NAICS industry level. All explanatory variables are defined in Appendix B.

	$Ave(T1)$	$P50(T1)$	$Ave(T2)$	$P50(T2)$	$Ave(T3)$	$P50(T3)$	T3-T1
Total Assets	711.66	21.70	760.43	22.36	650.24	20.24	0.03
Cash Flow	0.16	0.12	0.16	0.12	0.16	0.12	0.00
Leverage	0.61	0.63	0.61	0.63	0.61	0.63	0.00
Fixed Assets	0.28	0.19	0.32	0.23	0.28	0.19	0.00
Sales	2.34	1.98	2.25	1.89	2.35	2.00	-0.04**
Cash	0.10	0.05	0.10	0.05	0.10	0.05	0.00
Debt	0.31	0.28	0.34	0.31	0.32	0.28	0.003*
WorkCap	0.10	0.08	0.09	0.06	0.10	0.08	0.00

Table V: Credit Line Use In Panel A Column 1 presents OLS estimates from a regression of $\Delta Draw_{it}$ on $Cash\ Flow_{it}$. Columns 2 through 4 present 2SLS estimates of IV regressions of $\Delta Draw_{it}$ on instrumented $Cash\ Flow_{it}$. Columns 2 and 3 use *Abnormal Snow* as an instrumental variable, while Column 4 uses *Abnormal Snow P*95. All columns include county and four-digit NAICS x year-quarter fixed effects. Panel B presents OLS regressions that regress $\Delta Draw_{it}$ directly on *Abnormal Snow*. Since these tests do not all require financial data, in Panel B we scale $\Delta Draw_{it}$ by the beginning of period total loan commitment. Columns 1 through 3 use a sample that requires the same financial statement information as in Panel A. Columns 1 and 2 differ only in that Column 2 includes firm instead of county fixed effects. Columns 1 and 3 differ in that Column 3 adds firm-level control variables. Columns 4 and 5 expand the sample to all borrower-years for which we have bank loan information. Column 5 differs from Column 4 in that it includes firm instead of county fixed effects, instead of county fixed effects. All columns include four-digit NAICS industry x year-quarter fixed effects and use standard errors that are clustered at the four-digit NAICS industry level. All variables are defined in Appendix B.

Panel A: OLS and 2SLS

	$\Delta Draw_{it}$			
	OLS	*2SLS*	*2SLS*	*2SLS*
	(1)	(2)	(3)	(4)
$Cash\ Flow_{it}$	−0.0000	−0.407**	−0.425**	−0.524**
	(0.0028)	(0.173)	(0.189)	(0.259)
$Log(Assets)_{it-1}$	−0.0022***		−0.003***	−0.004***
	(0.0006)		(0.001)	(0.001)
$Fixed\ Assets_{it-1}$	−0.0132***		0.026	0.035
	(0.0035)		(0.017)	(0.023)
$Leverage_{it-1}$	0.0023		−0.031*	−0.039
	(0.0030)		(0.016)	(0.024)
$Sales_{it-1}$	0.0018***		0.016**	0.020**
	(0.0005)		(0.006)	(0.009)
$Cash_{it-1}$	−0.0231***		0.072	0.093
	(0.0049)		(0.042)	(0.060)
$Debt_{it-1}$	0.0084		0.010	0.010
	(0.0059)		(0.006)	(0.009)
$WorkCap_{it-1}$	−0.0033		0.007	0.009
	(0.0023)		(0.005)	(0.006)
Industry x Year-quarter FEs	YES	YES	YES	YES
County FE	YES	YES	YES	YES
R-Squared	0.115	.	.	.
Observations	102,742	102,742	102,742	102,742

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Panel B: Reduced Form

	$\Delta Draw_{it}$				
	(1)	(2)	(3)	(4)	(5)
$Abn.\ Snow_{it}$	0.031**	0.032	0.032**	0.027***	0.027*
	(0.014)	(0.021)	(0.014)	(0.008)	(0.016)
$Log(Assets)_{it-1}$			0.002***		
			(0.001)		
$Fixed\ Assets_{it-1}$			−0.009		
			(0.007)		
$Leverage_{it-1}$			0.007		
			(0.009)		
$Sales_{it-1}$			0.002***		
			(0.001)		
$Cash_{it-1}$			−0.081***		
			(0.011)		
$Debt_{it-1}$			−0.027***		
			(0.008)		
$WorkCap_{it-1}$			0.001		
			(0.008)		
Industry x Year-quarter FEs	YES	YES	YES	YES	YES
County FE	YES	NO	YES	YES	NO
Firm FE	NO	YES	NO	NO	YES
R-Squared	0.105	0.374	0.107	0.091	0.310
Observations	100,424	75,876	100,424	189,312	164,603

Table VI: Credit Line Size Column 1 presents OLS estimates from regressions of $\Delta Line\ Size_{it}$ on $Cash\ Flow_{it}$. Column 2 presents 2SLS estimates of IV regressions of $\Delta Line\ Size_{it}$ on instrumented $Cash\ Flow_{it}$, using *Abnormal Snow* as an instrumental variable. Columns 3 and 4 present OLS regressions that regress $\Delta Line\ Size_{it}$ directly on *Abnormal Snow*. Since these tests do not all require financial data, we scale $\Delta Line\ Size_{it}$ by the beginning of period total loan commitments. Here, we expand the sample to all borrower-years for which we have bank loan information. Column 4 differs from Columns 1 through 3 in that it includes firm fixed effects, instead of county fixed effects. All columns include four-digit NAICS industry x year-quarter fixed effects and use standard errors that are clustered at the four-digit NAICS industry level. All variables are defined in Appendix B.

	$\Delta Line\ Size_{it}$			
	OLS	*2SLS*	*Red.Form*	*Red.Form*
	(1)	(2)	(3)	(4)
$Cash\ Flow_{it}$	0.0195***	−0.526**		
	(0.0050)	(0.246)		
$Abn.\ Snow_{it}$			0.0709***	0.0722***
			(0.0129)	(0.0203)
$Log(Assets)_{it-1}$	−0.0022***	−0.0037***		
	(0.0005)	(0.0010)		
$Fixed\ Assets_{it-1}$	−0.0206***	0.0300		
	(0.0041)	(0.0217)		
$Leverage_{it-1}$	0.0064*	−0.0361		
	(0.0037)	(0.0240)		
$Sales_{it-1}$	0.0029***	0.0213**		
	(0.0005)	(0.0084)		
$Cash_{it-1}$	−0.0419***	0.0793		
	(0.0049)	(0.0563)		
$Debt_{it-1}$	0.0117***	0.0134		
	(0.0039)	(0.0141)		
$WorkCap_{it-1}$	−0.0064**	0.0062		
	(0.0028)	(0.0068)		
Industry x Year-quarter FEs	YES	YES	YES	YES
County FE	YES	YES	YES	NO
Firm FE	NO	NO	NO	YES
R-Squared	0.151	.	0.144	0.378
Observations	102,742	102,742	189,312	164,603

Standard errors in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table VII: Credit Line Slack This table partitions our reduced-form analysis on pre-existing credit line slack. Specifically, we partitions the sample on whether the borrower's beginning period credit line slack (=unused credit line commitments to total credit line commitments) is greater than the 25^{th} percentile of the respective distribution. Columns 1 and 2 (3 and 4) regress $\Delta Draw_{it}$ ($\Delta Line\ Size_{it}$) on *Abnormal Snow*. All columns include four-digit NAICS x year-quarter fixed effects. Panel A also includes county fixed effects, while Panel B includes firm fixed effects. The standard errors are clustered at the four-digit NAICS 2012 industry level. All variables are defined in Appendix B.

Panel A: County Fixed Effects

	$\Delta Drawn$		$\Delta Line\ Size$	
	Low Slack	*Slack*	*Low Slack*	*Slack*
	(1)	(2)	(3)	(4)
Abn. Snow	0.0594***	0.0084	0.1007***	−0.0008
	(0.0180)	(0.0100)	(0.0279)	(0.0182)
Observations	32,489	100,139	32,489	100,139
R-Squared	0.1855	0.0829	0.2549	0.0845
Industry x Year-qtr FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES

Panel B: Firm Fixed Effects

	$\Delta Drawn$		$\Delta Line\ Size$	
	Low Slack	*Slack*	*Low Slack*	*Slack*
	(1)	(2)	(3)	(4)
Abn. Snow	0.0542*	0.0152	0.0918***	0.0027
	(0.0275)	(0.0167)	(0.0336)	(0.0240)
Observations	22,319	83,941	22,319	83,941
R-Squared	0.4727	0.3414	0.5588	0.3862
Industry x Year-qtr FE	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES

Table VIII: Other Liquidity Management Tools This table presents 2SLS estimates of IV regressions of $\Delta Cash_{it}$, $\Delta FixedAssets_{it}$, $\Delta TradeCred_{it}$, and $\Delta TotalDebt_{it}$ on instrumented *Cash* $Flow_{it}$ and controls. We instrument for *Cash* $Flow_{it}$ with *Abnormal Snow* (using Column 2 of Table 2 as our first stage). All columns include four-digit NAICS x year-quarter and county fixed effects. The standard errors are clustered at the four-digit NAICS 2012 industry level. All variables are defined in Appendix B.

	$\Delta Cash_{it}$ (1)	$\Delta FixedAssets_{it}$ (2)	$\Delta TradeCred_{it}$ (3)	$\Delta Total\ Debt_{it}$ (4)
$Cash\ Flow_{it}$	0.181	0.059	0.012	−0.354*
	(0.119)	(0.168)	(0.098)	(0.203)
$Log(Assets)_{it-1}$	−0.0005	0.001	−0.0006**	−0.0005
	(0.0004)	(0.001)	(0.0003)	(0.0008)
$Fixed\ Assets_{it-1}$	−0.015	−0.017	−0.005	0.028
	(0.012)	(0.015)	(0.009)	(0.021)
$Leverage_{it-1}$	−0.001	−0.019	0.003	−0.006
	(0.010)	(0.016)	(0.008)	(0.019)
$Sales_{it-1}$	−0.004	−0.0005	−0.002	0.014**
	(0.004)	(0.006)	(0.003)	(0.007)
$Cash_{it-1}$	−0.131***	−0.024	0.006	0.021
	(0.027)	(0.036)	(0.023)	(0.046)
$Debt_{it-1}$	−0.017**	−0.003	−0.004*	−0.105***
	(0.008)	(0.003)	(0.002)	(0.018)
$WorkCap_{it-1}$	0.005	−0.019***	−0.009***	−0.013*
	(0.004)	(0.004)	(0.003)	(0.007)
Industry x Year-qtr FE	YES	YES	YES	YES
County FE	YES	YES	YES	YES
Observations	102,742	102,742	102,679	102,742

Standard errors in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table IX: Loan Interest Rates The dependent variables are $\Delta Line\ Interest\ Rate_{it}$ (Columns 1, 3, and 4) and $\Delta Interest\ Rate_{it}$ (Columns 2, 5, and 6). Columns 1 and 2 present second-stage 2SLS estimates in which cash flows are instrumented for with *Abnormal Snow*. Columns 3 through 6 regress the dependent variables directly on *Abnormal Snow*. Columns 1 and 2 include the same set of control variables as in column (3) of Table 5 Panel A. All columns include four-digit NAICS x year-quarter fixed effects. Columns 1, 2, 3, and 5 also include county fixed effects, while Columns 4 and 6 include firm fixed effects. The standard errors are clustered at the four-digit NAICS industry level. All variables are defined in Appendix B.

	$\Delta Line\ Rt$	$\Delta Rate$	$\Delta Line\ Rate$		$\Delta Rate$	
	(1)	(2)	(3)	(4)	(5)	(6)
$Cash\ Flow_{it}$	−0.051*	−0.024**				
	(0.026)	(0.012)				
Abn. Snow			0.0008**	0.0012***	0.0005**	0.0006*
			(0.0003)	(0.0004)	(0.0002)	(0.0003)
Firm Controls	YES	YES	NO	NO	NO	NO
Ind.-Year-Qtr.	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	NO	YES	NO
Firm FE	NO	NO	NO	YES	NO	YES
R-Squared			0.143	0.383	0.091	0.342
Observations	40,959	78,601	91,529	77,442	149,648	126,586

Table X: Non-Price Loan Provisions The dependent variables are (in Panel A) $\Delta Maturity_{it}$, (in Panel B) $\Delta FixedRate_{it}$, and (in Panel C) $\Delta Secured_{it}$. Column 1 of each panel presents second-stage 2SLS estimates where cash flows are instrumented for with *Abnormal Snow*. Columns 2 and 3 regress the dependent variable directly on *Abnormal Snow*. Column 1 includes the same set of control variables as in column (3) of Table 5 Panel A. All columns include four-digit NAICS x year-quarter fixed effects. Columns 1 and 2 also include county fixed effects, while Column 3 includes firm fixed effects. The standard errors are clustered at the four-digit NAICS industry level.

Panel A: Loan Maturity

	$\Delta Maturity_{it}$		
	$2SLS$	$Red.Form$	$Red.Form$
	(1)	(2)	(3)
$Cash\ Flow_{it}$	29.25***		
	(10.31)		
$Abn.\ Snow$		−0.740***	−0.894***
		(0.183)	(0.263)
Firm Controls	YES	NO	NO
Industry x Year-quarter FEs	YES	YES	YES
County FE	YES	YES	NO
Firm FE	NO	NO	YES
R-Squared	.	0.084	0.276
Observations	100,422	189,310	164,603

Panel B: Fixed Rate Loan

	$\Delta FixedRate_{it}$		
	$2SLS$	$Red.Form$	$Red.Form$
	(1)	(2)	(3)
$Cash\ Flow_{it}$	1.150***		
	(0.374)		
$Abn.\ Snow$		−0.019***	−0.022***
		(0.005)	(0.006)
Firm Controls	YES	NO	NO
Industry x Year-quarter FEs	YES	YES	YES
County FE	YES	YES	NO
Firm FE	NO	NO	YES
R-Squared	.	0.067	0.321
Observations	100,422	189,310	164,603

Panel C: Secured Loan

	$\Delta Secured_{it}$		
	$2SLS$ (1)	$Red.Form$ (2)	$Red.Form$ (3)
$Cash\ Flow_{it}$	-3.728***		
	(1.306)		
$Abn.\ Snow$		0.120***	0.124***
		(0.020)	(0.030)
Firm Controls	YES	NO	NO
Industry x Year-quarter FEs	YES	YES	YES
County FE	YES	YES	NO
Firm FE	NO	NO	YES
R-Squared	.	0.216	0.380
Observations	100,422	189,310	164,603

Table XI: Examination of Heterogeneity in Main Results This table partitions our reduced-form analysis on borrower total assets (Panel A), distance-to-lender (Panel B), and the loans rating (Panel C). In Panel A, large firms are those with over $100 million in total assets, while small firms are those with less than $100 million in total assets or unreported total assets. In Panel B, firms are considered near to (far from) their lender if the average distance between the borrower and the syndicated lending office of their lead managers is less than (more than) 100 miles. Panel C partitions the sample on whether the loan is rated BB or better according the lender's internal credit rating.Columns 1 through 4 (5 though 8) regress $\Delta Draw_{it}$ ($\Delta Line\ Size_{it}$) on *Abnormal Snow*. All columns include four-digit NAICS x year-quarter fixed effects. Odd (even) numbered columns also include county (firm) fixed effects. The standard errors are clustered at the four-digit NAICS 2012 industry level. All variables are defined in Appendix B.

Panel A: Borrower Total Assets Partition

	$\Delta Draw_{it}$				$\Delta Line\ Size_{it}$			
	Small		*Large*		*Small*		*Large*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abn. Snow	0.035***	0.041**	0.007	−0.021	0.083***	0.083***	0.063	0.049
	(0.009)	(0.019)	(0.023)	(0.033)	(0.014)	(0.024)	(0.044)	(0.062)
Ind.-Year-Qtr.	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	NO	YES	NO	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
R-Squared	0.102	0.322	0.130	0.359	0.165	0.400	0.166	0.404
Observations	149,326	126,829	38,829	33,717	149,326	126,829	38,829	33,717

Panel B: Distance-to-lender Partition

	$\Delta Draw_{it}$				$\Delta Line\ Size_{it}$			
	Near		*Far*		*Near*		*Far*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abn. Snow	0.119***	0.078**	−0.003	−0.004	0.301***	0.186**	0.004	0.018
	(0.024)	(0.036)	(0.013)	(0.017)	(0.059)	(0.084)	(0.022)	(0.025)
Ind.-Year-Qtr.	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	NO	YES	NO	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
R-Squared	0.123	0.343	0.115	0.328	0.152	0.394	0.179	0.411
Observations	54,012	46,522	99,536	87,024	54,012	46,522	99,536	87,024

Panel C: Loan Rating Partition

	$\Delta Draw_{it}$				$\Delta Line\ Size_{it}$			
	BBorBetter		*BorWorse*		*BBorBetter*		*BorWorse*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Abn. Snow	0.032***	0.025	0.007	−0.042	0.084***	0.084***	0.004	−0.059
	(0.010)	(0.017)	(0.020)	(0.041)	(0.014)	(0.020)	(0.035)	(0.067)
Ind.-Year-Qtr.	YES	YES	YES	YES	YES	YES	YES	YES
County FE	YES	NO	YES	NO	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES	NO	YES	NO	YES
R-Squared	0.101	0.337	0.148	0.427	0.161	0.409	0.174	0.473
Observations	153,667	129,746	34,133	21,360	153,667	129,746	34,133	21,360

Appendix A - Data Cleaning

We first clean data errors in the financial statement information in the loan-quarter panel. To minimize the effect of errors we exclude financial statement information if the financial statement date is missing or comes later than the data report date. We also exclude likely data errors by requiring that for each firm and financial statement date: 1) EBITDA does not exceed net sales, 2) fixed assets do exceed total assets, 3) cash and marketable securities do not exceed total assets, 4) long-term debt does not exceed total liabilities, 5) short-term debt does not exceed total liabilities, 6) tangible assets do not exceed total assets, 7) current assets do not exceed total assets, 8) current liabilities do not exceed total liabilities.

Next, to address the possibility that some large corporations are borrowing through their subsidiaries, for each borrower and financial statement date we only keep the financial statement information corresponding to the observation with the largest value of total assets. Given that the financials and physical location information we observe always correspond to the entity that is directly responsible for loan repayment, in the case of large firms the financial statement information could be that of a subsidiary instead of the ultimate parent company. For example, to the extent that for a given borrower-quarter one financial institution reports the financials of a corresponding subsidiary while another institution reports financials associated with the parent entity, then we will retain the financials of the parent entity. If, however, certain companies only borrow through their subsidiaries, we may understate the size of some firms in our sample.

Last, we correct errors related to the dollar units of reporting. In some cases the financial statement information may be reported in thousands of US dollars instead of raw dollar amounts as instructed. To address this potential reporting irregularity, we multiply all financial statement information by 1,000 if either the utilized loan exposure in a given reporting quarter exceeds total liabilities by a factor of 100 or more, or if total assets are less than $100,000. Given that the reporting criteria only includes loans larger than $1 million, it is highly unlikely that the borrower has total assets below $100,000.

Additionally, given that we rely on the time series aspect of the data, we require that currently-reported borrower total assets for the prior year are within 1% of the 1-year lagged value of currently-reported borrower total assets. This filter eliminates observations in which the Y-14 reporters switch reporting of financial statement information between subsidiaries and the parent company of the borrower.

Given our controls rely on both currently-reported lags of some of the financial variables as well as lags that we construct from the data, before we arrive at the final data set we also drop observations in which: 1) lagged operating income exceeds lagged sales, 2) lagged fixed assets exceeds lagged total assets, 3) lagged current liabilities exceeds lagged total assets, 4) lagged total liabilities do not exceed lagged total assets, 5) the lagged values of total liabilities are greater than or equal to zero. We also require that (6) the current and lagged values of the size of lines of credit do not exceed total assets, (7) the current and lagged values of the size of lines of credit do not exceed the corresponding values for total liabilities.[25]

[25] The final three filters, 5-7, do not materially affect our results, but we believe enhance the quality of data used in our estimation. Filter 7, the most influential of these filters requires that line size does not exceed total liabilities. Removing this filter leads to larger estimates of our main results and a sample that is approximately 20% larger. We apply this filter to be conservative as we do not want these borrowers with unusually large reported credit lines, which may correspond to data errors with respect to either the reported line size or reported liabilities, to skew our results.

Appendix B - Variable Definitions

Below we present variable definitions, the item numbers of data fields refer to Schedule H1 of the Y-14Q data on the Federal Reserve's website:

$https://www.federalreserve.gov/reportforms/forms/FR\_Y-14Q20160930\_i.pdf$

$\boldsymbol{Total\ Assets_{it-1}}$ – is defined as the first annual lag of the book value of total assets as of the current financial statement date, 'Total Assets Current Year' (item #70) data field in Y-14Q Schedule H1. To the extent that 'Total Assets Current Year' is missing, we replace it with the book value of total assets as of exactly one year prior to the current financial statement date, 'Total Assets Prior Year' (item #71).

$\boldsymbol{Cash\ Flow_{it}}$ – we primarily rely on the sum of 'Operating Income' (item #56) and 'Depreciation & Amortization' (item #57) to arrive at a measure of EBITDA. To the extent that the 'Operating Income' field is not populated in our data, we fill in missing values with the 'EBITDA' field that is overall available for a smaller fraction of the data. We then scale the resulting variable by $Total\ Assets_{it-1}$ to arrive at $Cash\ Flow$.

$\boldsymbol{Sales_{it-1}}$ is defined as the net sales from time $t-2$ to $t-1$, 'Net Sales Prior Year' (item #55) divided by total assets of firm i at time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Leverage_{it-1}}$ is defined as the first annual lag of the value of total liabilities of firm i, 'Total Liabilities' (item #80), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Fixed\ Assets_{it-1}}$ is defined as the first annual lag of the value of total fixed assets of firm i, 'Fixed Assets' (item #69), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{WorkCap_{it-1}}$ is defined as the first annual lag of the value of current assets of firm i, 'Current Assets Current' (item #66), minus the first annual lag of the value of current liabilities, 'Current Liabilities Current' (item #76)', minus first annual lag of the value of cash and marketable securities of firm i, 'Cash & Marketable Securities' (item #61). Then the resulting value is divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$. To the extent that 'Current Assets Current' and 'Current Liabilities Current' are missing, we replace it with 'Current Assets Prior Year' (item #67) and 'Current Liabilities Prior Year' (item #77) which are the values current assets and current liabilities exactly one year prior to the current financial statement date.

$\boldsymbol{Cash_{it-1}}$ is defined as the first annual lag of the value of cash and marketable securities of firm i, 'Cash & Marketable Securities' (item #61), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Debt_{it-1}}$ is defined as the first annual lag of the value of total debt of firm i, 'Short-Term Debt' (item #74) + 'Long-Term Debt' (item #78), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Lines_{it-1}}$ is defined as the first annual lag of the total value of credit line commitments of firm i ('Commitment Exposure Global' (item #24) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Draw_{it-1}}$ is defined as the first annual lag of the total value of drawn amount under all credit line commitments of firm i ('Utilized Exposure Global' (item #25) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Line\ Size_{it}}$ is defined as the annual change of the total value of credit line commitments of firm i ('Commitment Exposure Global' (item #24) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{Line\ Increase_{it}}$ is an indicator variable that takes the value of one whenever the total credit line commitments of firm i in year t exceed the total credit line commitments of firm i in year $t-1$.

$\boldsymbol{\Delta Draw_{it}}$ is defined as the annual change of the total value of drawn amount under all credit line commitments of firm i ('Utilized Exposure Global' (item #25) aggregated for each firm-quarter in our sample), divided by total assets of firm i also as of time $t-1$,

$Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Cash_{it}}$ is defined as the annual change of the value of cash and marketable securities of firm i ('Cash & Marketable Securities' (item #61)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Liabilities_{it}}$ is defined as the annual change of the value of total liabilities of firm i ('Total Liabilities' (item #80)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Debt_{it}}$ is defined as the annual change of the value of total debt of firm i ('Short-Term Debt' (item #74) + 'Long-Term Debt' (item #78)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta TradeCred_{it}}$ is defined as the annual change of the value of accounts receivable of firm i from year $t-1$ to year t ('A/R Current' (item #62) − 'A/R Prior Year' (item #63)) minus the annual change of accounts payable of firms i from year $t-1$ to year t ('A/P Current' (item #72) − 'A/P Prior Year' (item #73)), divided by net sales of firm i from time $t-2$ to $t-1$, 'Net Sales Prior Year' (item #55).

$\boldsymbol{\Delta Assets_{it}}$ is defined as the annual change of the value of total assets of firm i (we use 'Total Assets Current Year' (item #70) to build the current value of total assets), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta Fixed\ Assets_{it}}$ is defined as the annual change of the value of total fixed assets of firm i ('Fixed Assets' (item #69)), divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

$\boldsymbol{\Delta WorkCap_{it}}$ is defined as the annual change of the value of non-cash working capital of firm i ($WorkCap$) between years $t-1$ and t, divided by total assets of firm i also as of time $t-1$, $Total\ Assets_{it-1}$.

Internet Appendix for Weathering Cash Flow Shocks[1]

[1]Brown, James, Matthew Gustafson, and Ivan Ivanov, Internet Appendix to "Weathering Cash Flow Shocks," Journal of Finance [DOI STRING].

Table AI: Sales and Abnormal Weather: Industry Partitions This table contains estimated coefficients from an OLS regression of $Sales_{it}$ on *Abnormal Snow* in a model with identical controls to that in Specifications (2) and (4) of Table II. Each row in the table restricts the sample to the sector indicated in Column 1. Columns 2 and 3 present the estimates (and standard errors below in parentheses) for the coefficients on *Abnormal Snow* and *Abnormal Snow P*95, respectively. We include state and year fixed effects. The standard errors are clustered at the four-digit NAICS 2012 industry level. Borrower industry is defined in terms of the 2-digit NAICS code corresponding to each borrower. Borrowers with 2-digit NAICS codes of 31, 32, and 33 are classified as "Manufacturing"; 42 is classified as "Wholesale Trade"; 44 and 45 as "Retail Trade"; 48 and 49 as "Transportation"; 53 as "Real Estate"; 54, 55, and 56 as "Business Services"; 61 and 62 as "Education & Health"; 23 as "Construction'. All variables are defined in Appendix B.

All unreported industries comprise less than 4% of our sample totalling 103,261 observations.

	Ab. Snow (SE)	Ab. Snow P95 (SE)	% *Obs*	*Obs*
MANUFACTURING	0.021	0.031	23.6%	24,370
	(0.040)	(0.023)		
WHOLESALE	−0.091	−0.052	17.4%	17,927
	(0.079)	(0.041)		
RETAIL	−0.019	−0.001	14.0%	14,507
	(0.069)	(0.041)		
BUSINESS SERVICES	−0.006	0.068	9.5%	9,778
	(0.101)	(0.063)		
REAL ESTATE	−0.044	0.002	7.5%	7,729
	(0.085)	(0.044)		
CONSTRUCTION	0.158	0.107	7.1%	7,320
	(0.112)	(0.060)		
EDUCATION & HEALTH	−0.202	−0.129	4.6%	4,733
	(0.141)	(0.081)		
TRANSPORTATION	−0.051	−0.083	4.1%	4,217
	(0.111)	(0.062)		

Standard errors in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table AII: Autocorrelation of *Abnormal Snow* The table regresses *Abnormal Snow* on lagged *Abnormal Snow* within a county for county-years in the 2000-2010 time period (immediately prior the beginning of our sample period). All columns include county fixed effects and Columns 1 and 3 also include year fixed effects.

	Full Sample (1)	Full Sample (2)	Drop No Snow (3)	Drop No Snow (4)
Lagged (*Abnormal Snow*)	−0.017 (0.020)	−0.005 (0.020)	−0.031 (0.020)	−0.018 (0.020)
Year FEs	YES	NO	YES	NO
County FE	YES	YES	YES	YES
Observations	31,250	31,250	26,341	26,341

Robust standard errors in parentheses

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$

Table AIII: Change in Credit Line Drawn by Industry and Historical Snow This table contains the average change in drawn amount scaled by total committed bank debt from the previous year in the three terciles of average weather in the past 10 years. The statistics are partitioned by industry. Borrowers with 2-digit NAICS codes of 31, 32, and 33 are classified as "Manufacturing"; 42 is classified as "Wholesale Trade"; 44 and 45 as "Retail Trade"; 48 and 49 as "Transportation"; 53 as "Real Estate"; 54, 55, and 56 as "Business Services"; 61 and 62 as "Education & Health"; 23 as "Construction'.

All unreported industries comprise less than 4% of our sample.

	Q1	Q2	Q3	Q4
Tercile 1				
BUSINESS SERVICES	0.00	0.02	0.00	0.02
CONSTRUCTION	0.00	0.03	0.00	0.01
EDUCATION & HEALTH	0.00	0.01	0.01	0.01
MANUFACTURING	0.02	0.03	0.00	0.00
REAL ESTATE	0.00	0.01	0.00	0.01
RETAIL	0.00	0.03	−0.01	0.07
TRANSPORTATION	0.00	0.03	0.00	0.02
WHOLESALE	0.01	0.04	0.01	0.01
Tercile 2				
BUSINESS SERVICES	0.01	0.01	0.00	0.03
CONSTRUCTION	0.01	0.04	0.00	−0.01
EDUCATION & HEALTH	−0.00	0.00	0.00	0.02
MANUFACTURING	0.02	0.02	0.00	−0.00
REAL ESTATE	0.00	0.02	0.00	0.01
RETAIL	0.02	0.01	−0.02	0.08
TRANSPORTATION	0.01	0.03	0.01	0.01
WHOLESALE	0.02	0.03	0.01	−0.00
Tercile 3				
BUSINESS SERVICES	0.01	0.02	0.00	0.02
CONSTRUCTION	−0.00	0.06	−0.01	−0.01
EDUCATION & HEALTH	−0.01	0.00	0.01	0.02
MANUFACTURING	0.02	0.02	0.00	−0.01
REAL ESTATE	0.00	0.02	0.01	0.00
RETAIL	0.02	−0.00	−0.02	0.09
TRANSPORTATION	0.01	0.02	−0.00	0.00
WHOLESALE	0.02	0.04	0.00	−0.01

Table AIV: Credit Line Use: Robustness This table presents second-stage 2SLS results where the dependent variable is $\Delta Draw_{it}$. Column 1 replicates our 2SLS analysis excluding extreme abnormal snow events (i.e., those that are 3 standard deviations above or below the mean). Column 2 replicates our 2SLS analysis excluding areas that experience no snow events during our ten year benchmark period. Column 3 replicates the analysis including firm fixed effects. All columns include the same set of control variables as in column (3) of Table 5, four-digit NAICS x year-quarter fixed effects, and county fixed effects. The standard errors are clustered at the four-digit NAICS industry level. All variables are defined in Appendix B.

	$\Delta Draw_{it}$		
	Snow < 3SD	Snow > 0	Firm FEs
	(1)	(2)	(3)
$Cash\ Flow_{it}$	-0.562^{**}	-0.448^{**}	-0.749
	(0.262)	(0.189)	(0.696)
Firm Controls	YES	YES	YES
Industry x Year-quarter FEs	YES	YES	YES
County FE	YES	YES	NO
Firm FE	NO	NO	YES
Observations	94,061	89,914	77,662

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table AV: Credit Line Size: Robustness This table presents second-stage 2SLS results where the dependent variable is $\Delta Line\ Size_{it}$. Column 1 replicates our 2SLS analysis (Column 2 of Table V) using *Abnormal Snow* $P95$ as an IV for annual cash flows. Column 2 replicates our 2SLS analysis excluding extreme abnormal snow events (i.e., those that are 3 standard deviations above or below the mean). Column 3 replicates our 2SLS analysis excluding areas that experience no snow events during our ten year benchmark period. Column 4 replicates our 2SLS results excluding the firm-level control variables, while Column 5 replicates the analysis including firm fixed effects. All columns include four-digit NAICS x year-quarter fixed effects, and county fixed effects. The standard errors are clustered at the four-digit NAICS industry level. All variables are defined in Appendix B.

	$\Delta Line\ Size_{it}$				
	P95 IV (1)	Snow $<$ 3SD (2)	Snow $>$ 0 (3)	No Controls (4)	Firm FEs (5)
$Cash\ Flow_{it}$	-0.841^{**} (0.384)	-0.701^{**} (0.308)	-0.572^{**} (0.244)	-0.495^{**} (0.224)	-0.869 (1.081)
Firm Controls	YES	YES	YES	NO	YES
Ind.-Year-Qtr.	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	NO
Firm FE	NO	NO	NO	NO	YES
Observations	102,742	94,061	89,914	102,742	77,662

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table AVI: Cash Balances: Partitioning on Total Assets This table partitions our reduced-form analysis on borrower total assets. Large firms are those with over $100 million in total assets, while small firms are those with less than $100 million in total assets or unreported total assets. All columns regress $\Delta Cash_{it}$ on *Abnormal Snow*. All columns include four-digit NAICS x year-quarter fixed effects. Odd (even) numbered columns also include county (firm) fixed effects. The standard errors are clustered at the four-digit NAICS 2012 industry level. All variables are defined in Appendix B.

	$\Delta Cash_{it}$			
	Small		*Large*	
	(1)	(2)	(3)	(4)
Abn. Snow	−0.002	−0.003	−0.020**	−0.014
	(0.004)	(0.008)	(0.008)	(0.011)
Industry x Year-qtr FE	YES	YES	YES	YES
County FE	YES	NO	YES	NO
Firm FE	NO	YES	NO	YES
R-Squared	0.058	0.354	0.140	0.411
Observations	77,599	56,609	23,971	18,948

Table AVII: Partitioning 2SLS Results on Borrower Size This Table presents 2SLS estimates of IV regressions of $\Delta Draw_{it}$ (Columns 1 and 2), $\Delta Line\ Size_{it}$ (Columns 3 and 4), and $\Delta Cash_{it}$ (Columns 5 and 6) on instrumented $Cash\ Flow_{it}$ and controls. We instrument for $Cash\ Flow_{it}$ with *Abnormal Snow* (using Column 2 of Table 2 as our first stage). This table partitions the sample on borrower total assets, defining large firms (presented in even numbered columns) as those with over $100 million in total assets and small firms (presented in odd numbered columns) as those with less than $100 million in total assets or unreported total assets. All columns include the same set of control variables as in column (3) of Table 5, four-digit NAICS x year-quarter and county fixed effects. The standard errors are clustered at the four-digit NAICS 2012 industry level.

	$\Delta Draw_{it}$		$\Delta Line\ Size_{it}$		$\Delta Cash_{it}$	
	Small	*Large*	*Small*	*Large*	*Small*	*Large*
	(1)	(2)	(3)	(4)	(5)	(6)
$Cash\ Flow_{it}$	-0.827*	0.007	-0.992*	-0.095	0.115	0.378**
	(0.424)	(0.126)	(0.518)	(0.147)	(0.200)	(0.171)
Industry x Year-qtr FE	YES	YES	YES	YES	YES	YES
County FE	YES	YES	YES	YES	YES	YES
Observations	77,599	23,971	77,599	23,971	77,559	23,971